Computers in Human Behavior 119 (2021) 106731

Contents lists available at ScienceDirect

Computers in Human Behavior

journal homepage: http://www.elsevier.com/locate/comphumbeh

How smartphone use becomes problematic: Application of the ALT-SR model to study the predicting role of personality traits

L. Marciano *, P.J. Schulz, A.L. Camerini

Institute of Communication and Health, Faculty of Communication, Culture, and Society, USI Università Della Italiana, Via Giuseppe Buffi 13, 6900, Lugano, Switzerland

ARTICLE INFO

Keywords:
Adolescence
Problematic smartphone use
ALT-SR
Longitudinal
Personality
Gender

ABSTRACT

Smartphones have become a ubiquitous part of adolescents' life, and studies have repeatedly revealed a positive association between smartphone use (SU) and problematic smartphone use (PSU). However, longitudinal research investigating the reciprocal relationship among SU and PSU during adolescence are scarce, and studies that take into consideration personality traits as predisposing factors are lacking. This study used survey data collected annually over four years from 855 adolescents aged 11 at time 1 and distributed across 37 Swiss middle schools. An Autoregressive Latent Trajectory Model with Structured Residuals (ALT-SR model) was used to investigate *between*- and *within*-person effects over time. Additionally, gender and personality traits, measured according to the recently developed DSM-5 domains, were entered as predictors of the latent intercepts and slopes. The final model showed that, at the *within*-person level, SU significantly increased PSU at all four time points, but not *viceversa*. At the *between*-person level, the personality traits antagonism and negative affect significantly and positively predicted the latent intercepts, whereas being female, psychoticism, and disinhibition significantly and positively influenced the latent slopes. This study highlights the importance of investigating predisposing factors of PSU in adolescence, using advance statistical approaches. The results are discussed against the background of the I-PACE model on predisposing factors and mechanisms that lead to addictive behaviors such as PSU.

1. Introduction

Born at the advent of the 21st century, today's adolescents have grown up with digital media from an early age. As "digital natives" they have quickly become used to personalized and always accessible media contents, one-to-one or one-to-many communication through instant messaging, and the hands-on information and services digital devices such as smartphones offer to them (Palfrey & Gasser, 2011; Thomas, 2011). The popularity of smartphones manifests in their rapid diffusion, especially among tweens and teens. In Switzerland, 99 per cent of 12 to 19-year-olds owned a smartphone device in 2018, on which they spent, on average, almost 3.5 h during a weekday and 4.5 h during a weekend day (Süss et al., 2018, p. 83). In 2020, time spent on the smartphone increased by 40 min during a typical weekday and almost 2 h during a weekend day. This has been described as the highest increment from 2010, though, without any doubts, partly due to the ongoing COVID-19 pandemic and associated containment measures such as social distancing and distant learning (Süss et al., 2020, p. 76).

As smartphone use (SU) has increased steadily in this population - and the trend is likely to continue in the following years -, researchers have started to investigate the impact of smartphone-related screen time and problematic usage patterns on different developmental and health-related outcomes in adolescents. In one study, for example, increased levels of screen time were related to diminished psychological well-being in adolescents over the years (Twenge, Martin, & Campbell, 2018). At the same time, problematic smartphone use (PSU) is becoming a public health issue on its own (van Velthoven, Powell, & Powell, 2018), calling for further research on the different effects and predisposing factors of PSU. According to a recent meta-analysis (Sohn, Rees, Wildridge, Kalk, & Carter, 2019), one in four children and adolescents reported symptoms of PSU, which, according to previous reviews, has been identified as a correlate of anxiety, depression, stress, poor sleep and academic achievement, and other adverse health outcomes (e.g., Elhai, Levine, & Hall, 2019, 2017; Vahedi & Saiphoo, 2018). An important drawback of research on PSU among adolescents to date is that the majority of the studies relied on cross-sectional data with only a few investigating longitudinal relationships (e.g., Domoff, Foley, & Ferkel, 2020; Lo Coco et al., 2020; Zappulla, Pace, D'Urso, & Pace,

* Corresponding author. LAB (level 2), Via Buffi 13, 6900, Lugano, Switzerland.
E-mail address: laura.marciano@usi.ch (L. Marciano).

https://doi.org/10.1016/j.chb.2021.106731
Received 16 September 2020; Received in revised form 25 January 2021; Accepted 3 February 2021
Available online 7 February 2021

2019). Furthermore, researchers have paid little attention to the longitudinal investigation of predisposing factors such as personality traits and how they influence PSU and health-related outcomes in adolescence.

Previous reviews and meta-analyses on the association between personality traits and (problematic) media use, including PSU, summarized findings of primarily cross-sectional studies involving adult samples and using the Five-Factor Model of personality as the main framework (e.g., Carvalho, Sette, & Ferrari, 2018; Kayiş et al., 2016; Liu & Campbell, 2017; Marciano, Camerini, & Schulz, 2020; Twomey & O'Reilly, 2017). In addition, trait-like personality characteristics have been studied in adult samples, such as emotion regulation (e.g., Elhai, Tiamiyu, Weeks, Levine, Picard & Hall, 2018; Fu et al., 2020; Rozgonjuk & Elhai, 2019), Fear of Missing Out (FoMO; e.g., Elhai, Levine, et al., 2018; Elhai, Yang, & Montag, 2020; Elhai, Yang, Rozgonjuk, & Montag, 2020), and procrastination (e.g., Rozgonjuk, Kattago, & Täht, 2018; Wang et al., 2019). However, maladaptive personality traits conceptualized according to the Fifth edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM-5; APA, 2013) have been rarely considered (e.g., Gervasi et al., 2017) and no study to date investigated how they are related to SU and PSU in adolescence.

To better understand the phenomenon of PSU, it is now mandatory to take a comprehensive approach by investigating how PSU develops over time, particularly during the critical period of adolescence (Larsen & Luna, 2018), and which are the predisposing elements, e.g. personality traits, that can function either as risk or protective factors of PSU. To fill this gap, the aim of the present study was twofold: First, we aimed to investigate how SU can turn into PSU during adolescence by studying the longitudinal relationship between the two constructs over four time points, each one year apart, in a sample of early adolescents. Second, we aimed to explore how personality traits predict levels and growth trajectories of SU and PSU over time as well as their reciprocal relationship. To do so, we applied the Latent Curve Model with Structured Residuals (ALT-SR; Curran, Howard, Bainter, Lane, & McGinley, 2014), which is an extraordinarily flexible and powerful statistical tool for the analysis of developmental data. The ALT-SR model (Curran et al., 2014) offers a distinctive method through which a developmental hypothesis can be tested in a way that is more similar to the theory of adolescent development. In general, the ALT-SR model can be seen as an extension of the Random-Intercept Cross-Lagged Panel model (RI-CLPM), as it incorporates elements of growth modelling into a RI-CLPM (Hamaker, Kuiper, & Grasman, 2015), and both can be described as a "major precondition for drawing causal inferences from panel data" (Mund & Nestler, 2019, p. 12). The ALT-SR model has been used in recent research in the field of developmental psychology (e.g., Davis et al., 2019; Dunbar et al., 2019; Murray, Caye, et al., 2020; Murray, Eisner, & Ribeaud, 2020; Murray, Zych, Ribeaud, & Eisner, 2021). However, its use in the field of media effects is still scarce (e.g., Coyne, Rogers, Zurcher, Stockdale, & Booth, 2020; Davis et al., 2019a). Hence, by using such a method, we add to the few media effects studies and hope to encourage future research to make use of this powerful and flexible statistical approach to unscramble multilevel effects in developmental data. We hope that the study results may ultimately help to develop and refine intervention programs for adolescents that aim to inform and educate on conscious use of the smartphone, and to prevent PSU and related adverse outcomes.

2. Problematic smartphone use

2.1. Conceptualization of problematic smartphone use

PSU can be defined as a "behavioral addiction", a term introduced in 2010 from the DSM-5 Working Group, to describe diagnoses sharing similar features with substance-related and addictive disorders (American Psychiatric Association, 2013; K.P.; Rosenberg, 2014; World Health Organization, 2018). However, so far, only Internet Gaming Disorder has been included in the DSM-5 as a behavioral addiction which demands further research. Recently, the scientific literature started to focus on PSU, which, together with Internet Addiction Disorder (IAD), may also be described as a "technological addiction" (Griffiths, 1996). Although for some authors PSU does not meet the severity levels of those caused by substance-related addictions (Panova & Carbonell, 2018), PSU shares common features with more established behavioral addictions like IAD (Block, 2008; Chin & Leung, 2018; De-Sola Gutiérrez, Rodríguez de Fonseca, & Rubio, 2016; Griffiths, 1996; Jo et al., 2019; Lin, Lin, Yang, & Kuo, 2017; Shaw & Black, 2008; Zhitomirsky-Geffet & Blau, 2016). Based on the 11th revision of the International Classification of Diseases (ICD-11; WHO, 2018), and on the DSM-5 (APA, 2013), the criteria describing PSU include cognitive salience, withdrawal, tolerance, overuse, difficulty in regulating the use and persistent use despite negative consequences, mood modifications, and conflict, including decreased time for other activities (Jo et al., 2019).

Cognitive salience refers to the tendency to think about the smartphone, even when not used at that moment. For example, salience may involve thinking about upcoming notifications or messages. Withdrawal includes symptoms of anxiety, distress, irritability, and pressure to check notifications which occur when the person is unable to reach his/her phone (Fernandez, Kuss, & Griffiths, 2020). This dimension is closely linked to "nomophobia", which refers to discomfort, nervousness or anguish caused by being out of contact with the mobile phone (Bragazzi & Del Puente, 2014). In addition, withdrawal is related to FoMO (Elhai, Levine, Dvorak, & Hall, 2016) defined as "a pervasive apprehension that others might be having rewarding experiences from which one is absent" (Przybylski, Murayama, DeHaan, & Gladwell, 2013, p. 1841), promoting a constant need to stay connected with others. Thus, withdrawal symptoms may arise as being offline prevented from following the latest events and experiences of others and increases the feeling of being left out (Fernandez et al., 2020). This can also be represented by the "eye-opener" behavior (Lin et al., 2017), describing the pattern of checking the phone as the eyes opened first in the morning, after sleep. Tolerance implies augmented time spent on the smartphone to reach the same amount of gratification as before, which is reflected in increased duration and frequency of SU. However, some authors outlined that this dimension is critical since it may also reflect cultural changes promoting the use of the device for many daily life activities (Lin et al., 2017). Although, the time spent on the device is not a problematic behavior *per se* (Billieaux et al., 2015), an excessive amount of time spent on the smartphone has been related to PSU (e.g., Aljomaa, Qudah, Albursan, Bakhiet, & Abduljabbar, 2016; De-Sola Gutiérrez et al., 2016; Gökçearslan, Mumcu, Haşlaman, & Çevik, 2016), and longitudinal studies have demonstrated that higher levels of SU predict PSU over time (Camerini & Marciano, 2019; Haug et al., 2015). Overuse is also related to the loss of control, hence difficulties in regulating and reducing SU when needed. Similarly, persistent use describes situations where a person continues to use the smartphone despite negative consequences such as poor sleep and being late for other activities. Mood modification involves the use of the smartphone to regulate mood and alleviate stress. Along this line, the access to the device's contents and apps serves as a coping strategy for negative emotions and as a tool to escape from problems. Finally, conflict includes problems and discord with close people (e.g., family and friends) as well as in the context of other activities (e.g., at work/school, sports, and hobbies) and also within the individual (e.g., intrapsychic conflict or feelings of lack of control) due to too much time spent with the smartphone. Problematic consequences are also related to the interference with other activities, important for the person or his/her future.

According to recent theories like the Interaction of Person-Affect-Cognition-Execution (I-PACE) model (Brand et al., 2016, 2019), different factors, such as cognition, personality, existing psychopathology, and motives for SU, determine the actual situation of the person, which can lead to PSU. In the beginning, the engagement in smartphone activities may be primarily driven by impulsivity, described as a

maladaptive predisposition towards quick reactions to respond to urges and impulses, reduced inhibition skills, and difficulty in delaying reward (Rosenberg, 2014). Brief, repetitive checking of the smartphone and the gratifying content it delivers act as positive reinforcements for the user (Oulasvirta, Rattenbury, Ma, & Raita, 2012). In a subsequent stage, possible problems in self-control and disinhibition (Grant, Brewer, & Potenza, 2006; Stein, Hollander, Simeon, & Cohen, 1994), together with conditioning processes, may lead to compulsive use. As previously mentioned, compulsive behaviors are acted to distract oneself from difficulties, regulate mood, and avoid negative emotions. Compulsive patterns are interrelated with the need to be constantly online and available to others (Halfmann & Rieger, 2019). They are fostered by the portability and easy accessibility of the smartphone. Compared to tablets and laptops, these unique features and the constant availability of personalized contents (Oulasvirta et al., 2012) may augment distractability and functional impairment, since the smartphone may interfere anywhere and at any time. The persistent and perseverative use of the smartphone may be perceived as unpleasant as it interferes with other activities, e.g., work and school duties and cognitive tasks (Cho & Lee, 2017; Hartanto & Yang, 2016; Martini, Heinz, Hinterholzer, Martini, & Sachse, 2020; Ward, Duke, Gneezy, & Bos, 2017; Wilmer, Sherman, & Chein, 2017). Its persistent use of the smartphone has also been related to phenomena like phubbing (Chotpitayasunondh & Douglas, 2016), and even risky behaviors (kita & Luria, 2018).

The shift from impulsivity to compulsivity is a core aspect of many addictions (Brewer & Potenza, 2008), and impulsivity-compulsivity can be considered two key factors that influence PSU. As in substance-use disorders, impulsive traits are pivotal features in starting the behavior, while compulsive features follow afterwards (Dell'Osso, Altamura, Allen, Marazziti, & Hollander, 2006; Raj & Verdejo-Garcia, 2020; Brand et al., 2019). In the I-PACE model, predisposing variables, including temperamental features alongside genetics, childhood experiences, psychopathology, and general coping style, expose "some" individuals (i.e., the more "at risk") to develop PSU (Brand et al., 2019).

Furthermore, previous studies showed that negative affect is a key component of addictive behaviors (Cuzen & Stein, 2014; Di Nicola et al., 2010), especially in the starting and maintaining phase (Kassel et al., 2007). Similarly to substance-use disorders, SU, and subsequentially PSU, regulates mood and acts as a stress-coping and self-medication tool (Elhai, Yang, & Montag, 2020; Flynn, Thériault, & Williams, 2020; Squires, Hollett, Hesson, & Harris, 2020). PSU promotes the possibility to "escape from oneself," which explains parts of the excessive use, specifically in the case of playing smartphone games and engaging in passive social media activities (Kwon, Chung, & Lee, 2011). The cognitive and affective response to media use, together with the gratifications obtained, can foster subsequent use. Managing negative emotions is not the only motivational process in PSU. The use of multiple and very different apps is a sign that PSU is associated with other motivations too, e.g., communication, entertainment, self-promotion, or information seeking. This distinguishes PSU from Online Gaming Disorder, which involves the exclusive use of (social) gaming apps (Lin et al., 2017). However, recent works, using trace data through apps installed in participants' devices, showed that PSU is indeed related to very specific usage patterns and their underlying motivations, such as the frequency of use (Lin et al., 2016; Marciano & Camerini, 2020), which is an indicator of (compulsive) checking behavior and a predictor of withdrawal symptoms, which are part of the concept of PSU. Furthermore, the consumption and interaction with social apps (e.g., Instagram, Tinder; Noe et al., 2019) seems to be the main driver of prolonged screen time, through infinite scrolling behaviors and quick checks of notifications.

2.2. Smartphone use as a predictor of problematic smartphone use

One important question to understand is what turns SU into PSU, particularly when one considers drivers of SU, like seeking social connections and information, that are not problematic *per se*. In fact, some authors questioned the existence of IAD and PSU (Aboujaoude, 2017; Billieux, Schimmenti, Khazaal, Maurage, & Heeren, 2015; Mihordin, 2012), stating that some normal activities risk to be over-pathologized only because they are carried out excessively, without considering (i) what excessive use really is since people are increasingly online, (ii) which problematic behaviors are triggered by the device or the online platform, including the psychological processes that sustain PSU, and (iii) proximal causes (such as ongoing psychological problems and risk factors). Despite the existence of these critics to the construct of PSU (and other technological addictions), some features of SU (e.g. the impulsive-compulsive use to seek gratification and managing emotions) have been constantly highlighted as particularly problematic for the user, since they may lead to poor social and health outcomes. As Griffiths (2005, p. 195) stated: "the difference between an excessive healthy enthusiasm and an addiction is that healthy enthusiasms add to life whereas addictions take away from it". This is particularly true in younger generations (Haidt & Allen, 2020), especially in the period of early adolescence, during which the risk of developing psychological problems is higher (Costello, Copeland, & Angold, 2011) and cognitive control processes are still immature (Steinberg, 2010).

A major challenge in research on the interrelation between SU and PSU is the validity of their measures. Especially in the context of SU, most studies to date relied on self-report data, which are prone to systematic biases, including, among others, recall bias, estimation bias, and social desirability bias (Boase & Ling, 2013; de Reuver & Bouwman, 2015; Krumpal, 2013). These biases make it hard to draw valid conclusions on which type of media use and how much can be described as problematic (Ellis, 2019; Kobayashi & Boase, 2012; Rozgonjuk, Pruunsild, Jürimäe, Schwarz, & Aru, 2020). Observational measures, including digital trace data, for example through apps directly installed on the smartphone, seem to overcome these biases, yet they are themselves not free from technical and logistical challenges and introduce other biases such as a high selection bias (Stier, Breuer, Siegers, & Thorson, 2019) due to the seemingly invasive nature of data collection. A compromise is the use of Ecological Momentary Assessments (EMAs) that allow measuring SU through short questions repeated multiple times a day for a short period (e.g., one or two weeks). EMAs are increasingly used in research with adolescents (Heron, Everhart, McHale, & Smyth, 2017) and, more recently, in the context of digital media use (Beyens, Pouwels, Driel, Keijsers, & Valkenburg, 2020; Beyens et al., 2020a). Yet, they are cost-intensive, based on comparably small samples, and require a high commitment from participants. The response burden makes EMAs prone to systematic drop-out, delayed responding, or response patterns, showing once again that researchers are far from having a "gold standard" measure of SU. Thus, they need to carefully evaluate which measure to use and discuss its limitations when interpreting their study findings. That said, self-report measures of the duration or frequency of SU have been applied in studies looking at PSU (e.g., Camerini, Gerosa, & Marciano, 2020; Duke & Montag, 2017; Haug et al., 2015; Škařupová, Ólafsson, & Blinka, 2016), which facilitates the comparison and discussion of results across studies on the topic.

3. (Problematic) smartphone use in adolescence

Knowing about the developmental patterns and interrelations of SU and PSU is particularly relevant when it comes to adolescents, since (P)SU may influence adolescents' neural, social, and emotional development (Odgers, 2018). During the period of adolescence (approximately 12–18 years old), brain regions undergo significant changes, which are influenced by biological and environmental factors (Burnett, Sebastian, Cohen Kadosh, & Blakemore, 2011; Larsen & Luna, 2018). Adolescents need to reach psychosocial autonomy (Steinberg, 2016), promoted by the development of self-identity and by their capacities to begin and maintain meaningful relationships with peers. The way in which an adolescent perceives him- or her-self is shaped by diverse components.

Self-identity, including self-esteem, depends largely on how others perceive and react to his/her behavior (e.g., through the mechanism of the "looking-glass self"; (Cooley, 1902). Hence, the sphere of peers gains more influence, as adolescents spend more time with those of their age and are more sensitive to social evaluation (Albert, Chein, & Steinberg, 2013; Somerville, 2013). During adolescence, the smartphone plays a significant role (Crone & Konijn, 2018) since it allows to stay in contact with others. Weak and strong social ties are maintained through online communication (Valkenburg & Peter, 2007), thus incrementing the fundamental role of the smartphone as a gateway to social activities (Valkenburg & Piotrowski, 2017). In general, SU is related to self-disclosure, peer-community, social support, and social bond (RSPH, 2017). In particular, online communication is used to connect with already existing friends, and sometimes also to start relations with strangers. For some, particularly anxious adolescents, the smartphone-based communication may help them to reduce social anxiety and shyness (e.g., "social compensation hypothesis"), whereas for more extraverted, online communication may ultimately foster their already existing personal relationships (e.g., "rich-get-richer hypothesis") (Valkenburg & Peter, 2007).

In addition, SU is an opportunity for adolescents to entertain themselves and seek rewards. Compared to children and adults, the adolescent brain shows a more pronounced and sustained response (i.e., more dopamine release) to gratifying contents, especially if these contents involve a social component (Galván, 2013). Indeed, there is a peak in reward-seeking behaviors during these years (Galván, 2013), however, self-control skills are still low. According to Allaby and Shannon (2020), smartphones are often used by adolescents to "kill" time, i.e. as an entertainment tool in boring moments, *via* the use of social media and streaming apps. Similarly, adolescents feel more urge to check their smartphones to stay in contact with others, which eventually may result in distraction by the smartphone, not only during studying hours but also while adolescents are engaged in leisure activities. These reasons and mechanisms may potentially lead to PSU in adolescence.

In a large-scale cross-sectional study among adolescents in Switzerland, Haug and colleagues (2015) found an association between PSU and longer use of the device during a typical weekday, but also with shorter duration of time until first smartphone use in the morning and preferred SU for social networking. In a similar fashion, Elhai, Dvorak, Levine, and Hall (2017) found that PSU is related to content consumption and social SU, including social networking, although the effect is stronger for content consumption, i.e. website browsing, listening to music, and watching videos. On the contrary, another study has identified social use of the smartphone as a particular driver of PSU among adolescents (Camerini et al., 2020). Furthermore, a qualitative study (Throuvala, Griffiths, Rennoldson, & Kuss, 2019) highlighted six motivational processes to use the smartphone and social media. Some of them were more practical oriented, such as the facilitation of communications functions, the symbiotic relationship with the phone and with others through online media, as well as the digital omnipresence. Whereas, others were more oriented to reach the psychosocial autonomy, like the idealization/normalization of the self and others, the comparison with peers, validation of the self, and emotion regulation.

Thus, although SU can be driven by motivational processes typical for this developmental period, it may turn into PSU. Studying PSU during adolescence is critical as it has been associated with many adverse psycho-physical outcomes, like depression and anxiety, sleep problems and risky behaviors (Albert et al., 2013; Coyne et al., 2020; Elhai et al., 2017; Hale & Guan, 2015; Sohn et al., 2019).

4. The role of personality traits

An important aspect of the I-PACE model is that the development of PSU happens when individuals' predisposing variables meet specific situations of media use. An important predisposing factor is personality and trait vulnerability. For many years, conceptualizing trait vulnerability before 18 years of age has been a challenge (Cohen, 2008). However, in 2013, the DSM-5 introduced in section III ("Emerging Measures and Models") a new approach to assess personality traits and to explore their development over time. In particular, the new nosology includes 25 specific elements of maladaptive personality, grouped into five broad domains, each of them distributed along a continuum: 1) negative affectivity versus emotional stability, 2) detachment versus extraversion, 3) antagonism versus agreeableness, 4) disinhibition versus conscientiousness, and 5) psychoticism versus lucidity (Krueger & Markon, 2014). These dimensions very well point towards some key components of PSU. For example, negative affectivity refers to the frequent experience of negative emotions, including behavioral and interpersonal problems to deal with them, whereas detachment represents the avoidance of socio-emotional experiences, including interactions with peers. Antagonism refers to features pertaining to narcissism, i.e. having an exaggerated sense of self-importance and lack of empathy towards others' emotions. Disinhibition is characteristic of a person-oriented toward immediate gratifications and impulsive behaviors. Finally, psychoticism is related to unusual cognitions and thoughts, mainly experienced in dissociation with reality. However, the use of this promising personality model is still at the beginning. A recent study (Ciccarelli, Nigro, Griffiths, D'Olimpio, & Cosenza, 2020) found that antagonism and disinhibition dimensions predicted gambling behaviors in a sample of Italian adolescents. These two personality dimensions were also found to correlate with behavioral problems, such as bullying (Romero & Alonso, 2019, pp. 263–270). In the same study, negative affect, detachment, and psychoticism were found to be related to emotional dissatisfaction, described as the presence of negative emotions, which has been identified as a motivational factor of SU earlier in this paper. Focusing on data from young adults (Gervasi et al., 2017) found that negative affect, disinhibition, and psychoticism predicted Internet addiction These results were in line with using the Internet to escape from negative emotions and as a self-medication tool, as well as the lack of control in problematic Internet users. Less integrated, psychotic people considered the online world as a place, in which real and illusional aspects can be merged (Rosegrant, 2012), providing an integration of internal and external experiences. In another study, low levels of detachment were found to predict the use of social media to mainly communicate with others, whereas people high in antagonism and disinhibition tended to use social media platforms to pass the time or search for relationships, thus seeking immediate satisfaction for needs and overlooking social norms (Perugini & Solano, 2020). Negative affect and psychoticism were also found to predict problematic Internet use in young adults, since the Internet may be seen as a "psychic retreat to prevent the overwhelming affect from emerging into consciousness" (Schimmenti et al., 2019, p. 11). One study focused on Internet gamers and found that all sub-dimensions of personality, together with positive reinforcement and avoidance expectancies, predict problematic gaming behaviors (Laier, Wegmann, & Brand, 2018).

To summarize, research on the new DSM-5 personality domains has been carried out mainly in adults and primarily in the context of problematic Internet use and online gaming behaviors. To date, no study has applied this conceptualization to PSU in adolescents. However, this step is necessary to obtain a better understanding of the phenomenon and to identify which traits render adolescents more vulnerable and likely to develop PSU (Carvalho et al., 2018). Furthermore, it is important to underline that adolescence is a developmental period where personality traits are gradually consolidated. Thus, the vast majority of longitudinal research in adolescents is very short in nature, and it does not focus on a comprehensive developmental period. At the same time, previous literature on PSU relied on traditional techniques, which fail in distinguishing *between*-from *within*-person effects. As developmental processes occur in the same individual, it is pivotal to differentiate the effects not only between adolescents who use more or less the smartphone, but also within the same individual when he/she starts to spend more time online above their own typical levels.

4.1. Study aims

To overcome the gap in the scientific literature, the aim of the present study is to: (i) investigate how SU and PSU develop over time; (ii) examine how personality traits influence levels and growth trajectories of SU and PSU, in particular we are interested in which personality traits can also fuel a shift from a non-problematic to a problematic use. To fulfil these aims, an ALT-SR model (Curran et al., 2014), which allows to isolate the *between*- and *within*-person component over time, modeling both intercepts and slopes of the two constructs, will be implemented. Based on previous literature investigating the link between SU and PSU, as well as previous studies investigating the PID-5 in the context of other behavioral addictions such as IAD and Gaming Disorder, we elaborated the following hypotheses:

H1: SU and PSU increase over time, and they influence each other, i.e. higher levels of SU predict higher levels of PSU and *vice versa*;

H2: Among the different personality traits, disinhibition, antagonism, psychoticism, and negative affectivity predict higher levels of SU and PSU over time (both intercepts and slopes), whereas detachment is negatively related with them.

By modelling how personality traits influence both SU and PSU over time, we ultimately shed light on which of the included variables contribute more to the development of PSU in adolescents, both directly and indirectly through SU.

5. Methods

5.1. Data collection

In the current study, we used data from wave 3 to 6 (following T1, T2, T3, and T4) of the ongoing MEDIATICINO (www.mediaticino.usi.ch) longitudinal study. Data collection was repeated annually with T1 in spring 2016 (grade I of middle school), T2 in spring 2017 (grade II), T3 in spring 2018 (grade III), and T4 in spring 2019 (grade IV). At T1, a paper-and-pencil questionnaire was handed out to randomly selected students across 35 public and two private middle schools, who are representative of pupils born in 2004/5 in Ticino, Southern Switzerland. Students were asked to complete the questionnaire by themselves during a moment of individual study at school. A teacher was present to provide further instructions upon request. Of the distributed questionnaires each year (n = 1492 at T1, n = 1460 at T2, n = 1419 at T3, and n = 1391 at T4), schools returned 1375 successfully completed questionnaires at T1 (92%), 1307 at T2 (98%), 1374 at T3 (97%), and 1224 at T4 (88%). Sample attrition was mainly due to students being absent during the day of data collection, students' dropouts of school, or change of school. Data from the four waves were matched with the help of a unique identifier assigned to each student name by the regional education administration. Teachers with access to both the identifier and the student name distributed the labelled questionnaires and collected all completed forms with the instruction to seal them in an envelope in front of the students and to send them directly back to the research team. Given that this procedure assured anonymity of the collected data and thereby sufficiently addressed ethical considerations regarding privacy, the regional education administration approved the study design. Further details on the longitudinal study procedure are reported elsewhere (Camerini, Schulz, & Jeannet, 2018).

5.2. Analytical sample

The analytical sample included 879 students who participated in all four waves and had less than 10% of missing data in the scales included in the analyses. Since data were missing at random (MAR), we used a Bayesian regression imputation method and a predictive mean matching model, to impute missing values. Finally, outliers, defined as ± 3.5 standard deviations from the mean, were removed (n = 24), resulting in a total of 855 participants included in the main analyses. Based on T1 data, participants were 11 years old (M = 11.36, SD = 0.55) and 53.7% of them were female (n = 459). The comparison of the analytical sample with students who dropped out after T1 revealed that the analytical sample included more females ($\chi^2 = 16.390$, $p < .001$). No differences were reported for SU, whereas dropped participants indicated higher levels of PSU at T1 ($M_{analytical} = 2.06$, $SD_{analytical} = 0.98$; $M_{dropped} = 1.88$, $SD_{dropped} = .83$, t = 2.938, p = .003; $t = 2.938$, $p < .001$).

5.3. Measures

All measures of this study are based on self-report. Measures were translated from English into Italian. Independent back-translation was performed to assure the linguistic validity of the translated measures. Means, standard deviations, and reliability measures for each concept and wave are summarized in Table 1.

Smartphone Use (SU) was measured asking participants the following two questions: "How much time do you usually use the smartphone on a typical school day/weekend day?". For each question, students estimated their daily smartphone use by choosing one option on a scale with nine-time interval: 0 ″never", 1 ″up to 0.5 h", 2 ″between 0.5 and 1 h", 3 ″between 1 and 1.5 h", 4 ″between 1.5 and 2 h", 5 ″between 2 and 3 h", 6, "between 3 and 4 h", 7 ″between 4 and 5 h", and 8 ″5 or more hours". The weighted mean between a typical school day and a typical weekend day [(time spent on the smartphone on a school day*5 + time spent on the smartphone on a weekend day *2)/7] was used as an approximate measure of smartphone use in terms of hours per day ($r > 0.79$ at each wave, see Table 1).

Problematic Smartphone Use (PSU) was assessed with the Short Version for adolescents of the Smartphone Addiction Scale (SAS-SV; Kwon et al., 2013), which has proven to have good validity and reliability (see Kwon et al., 2013 for more details), and which is based on the Smartphone Addiction Scale (SAS; Kwon et al., 2013a). The scale consists of ten items measured on a scale from 1 (strongly disagree) to 6 (strongly agree), which tackle different dimensions of PSU: cognitive salience (e.g. "Having my smartphone in my mind even when I am not using it"), withdrawal (e.g., "Feeling impatient and fretful when I am not holding my smartphone"), tolerance (e.g. "Using my smartphone longer than I had intended"), overuse (e.g., "Constantly checking my smartphone so as not to miss conversations between other people on Twitter or Facebook"), and conflict (e.g., "Missing planned work due to smartphone use"). All items were averaged to obtain an overall measure for each time point with higher values indicating higher levels of PSU ($\alpha > 0.81$ for each wave, see Table 1).

Personality Traits were measured at two-time points (T3 and T4) with 24 items from the "Personality Inventory for DSM-5, Brief Form (PID-5-BF)" for children age 11–17. They include: Negative Affect (5 items), Detachment (5 items), Antagonism (5 items), disinhibition (5 items), and Psychoticism (4 items). Answer options ranged from 1 ″Often false" to 4 ″Often true". Confirmatory factor analysis with diagonally weighted least squares estimator (DWLS) for categorical variables (Bollen & Long, 1993) confirmed the five-factor model at both times ($CFI_{T3} = 0.928$, $RMSEA_{T3} = 0.075$, 90% CI [0.071, 0.078], $SRMR_{T3} = 0.084$; $CFI_{T4} = 0.920$, $RMSEA_{T4} = 0.084$, 90% CI [0.081, 0.088], $SRMR_{T4} = 0.094$). The Cronbach's alphas for disinhibition ($\alpha_{T3} = 0.70$; $\alpha_{T4} = 0.72$), negative affect ($\alpha_{T3} = 0.73$; $\alpha_{T4} = 0.73$), psychoticism ($\alpha_{T3} = 0.76$; $\alpha_{T4} = 0.78$), detachment ($\alpha_{T3} = 0.63$; $\alpha_{T4} = 0.64$), and antagonism ($\alpha_{T3} = 0.71$; $\alpha_{T4} = 0.74$) were generally good, although not excellent, and reflect the ones found by a previous study on Italian adolescents (Fossati, Somma, Borroni, Markon, & Krueger, 2017). After preliminary analyses were performed to test if and how personality traits would change across time points (see Table 2 in Appendix A), the average values of the two waves for each subdimension were entered as covariates in the final model.

Gender was measured as 0 = "male" and 1 = "female" and added in the final analyses as a covariate.

Table 1
Bivariate correlation coefficients among all concepts.

	M (SD)	Reliability measure	1	2	3	4	5	6	7
1 SU use at T1	2.04 (1.68)	.822[r] *	1						
2 SU use at T2	3.05 (1.93)	.794[r] *	.525*	1					
3 SU use at T3	3.76 (1.94)	.823[r] *	.430*	.466*	1				
4 SU use at T4	4.26 (1.84)	.832[r] *	.336*	.411*	.540*	1			
5 PSU at T1	1.86 (.81)	.815 [α]	.482*	.284*	.286*	.216*	1		
6 PSU at T2	2.00 (.84)	.821 [α]	.385*	.521*	.332*	.283*	.462*	1	
7 PSU at T3	2.01 (.85)	.865 [α]	.199*	.278*	.388*	.247*	.309*	.362*	1
8 PSU at T4	1.99 (.84)	.882 [α]	.241*	.257*	.276*	.301*	.278*	.349*	.474*

*Note: n = 855, SU = Smartphone Use, PSU = Problematic Smartphone Use, T1 = Time 1, T2 = Time 2, T3 = Time 3, T4 = Time 4, *p<.001*; [r] = Pearson's r; [α] = Cronbach's α

Table 2
Model comparison.

	Description	Δχ2	df	p	ΔRMSEA	SRMR	ΔAIC	ΔBIC	BAYES FACTOR	Posterior Probability of H1
0. Baseline with no constraints										
cfr 0	1. Autoregressive paths	0.907	10	0.923	0.023	0.031	6.937	25.941	BF01 = 429552.8	pr (H1|D) = 0.999
cfr 1	**2. Auto-regressive + Cross-lagged paths**	**15.02**	**14**	**0.005**	**0.002**	**0.035**	**−9.66**	**9.345**	**BF12 = 106.96**	**pr (H2|D) = 0.990**
cfr1	3. Auto-regressive + Within-time covariances	27.983	12	<.001	−0.01	0.038	−21.876	−12.373	BF13 = .002	pr (H3|D) = 0.002
cfr2	4. Auto-regressive + Cross-lagged + Within-time covariance	29.767	16	<.001	−0.004	0.041	−14.04	−4.538	BF24 = .103	pr (H4|D) = 0.093

Legend. Δ = value of previous model – value of actual model. D = posterior probability of H1 = BF/(BF+1). Chosen model in bold.

6. Analytical plan

First, we conducted independent samples *t*-tests and Pearson's χ^2 statistic to check whether the analytical sample ($N_{analytical}$ = 855) differed significantly from students who dropped out after T1 ($N_{dropped}$ = 496) by comparing gender prevalence and their answers to the concepts measured at T1.

Second, we tested measurement invariance for the latent constructs of PSU with respect to gender and over time. Once the configural invariance between males and females was established, weak (constraining factor loadings), strong (constraining both factor loadings and intercepts), and strict (constraining factors loadings, intercepts, and residuals) invariance has been tested, following the approach by Hirschfeld and Von Brachel (2014). To compare the nested models, chi-square difference tests were calculated, but, due to its sensitivity to large sample sizes, other fit indices were evaluated (Chen, 2007; Cheung & Rensvold, 2002). In particular, models were compared, considering the following combination of cut-offs: ΔCFI should be below 0.01 (Cheung & Rensvold, 2002) and ΔRMSEA should be below 0.015 (Chen, 2007). If some parameters (e.g., factorial loadings or intercepts) are not equal across groups, partial measurement invariance would be considered (Byrne, Shavelson, & Muthén, 1989). Additionally, longitudinal invariance across the four data points for the measure of PSU was analyzed (Hirschfeld & Brachel, 2014).

Intra-class correlation coefficients (ICCs) of PSU and SU were further calculated using, the "ICC" 2.3.0 package in R, to evaluate the within- and between-person source of variance across the four waves. ICCs represent here the percentage of variance in the repeatedly measured variable, which is related to individual, trait-like, differences among participants, i.e. between-person variance. The remaining percentage of variance can be explained by within-person differences over time. The ALT-SR model allows differentiating between these two levels of variance from wave to wave.

After these preliminary analyses, we tested the ALT-SR model (following the procedure by Mund & Nestler, 2019, see Fig. 1) using the LAVAAN 0.6–7 package (Rosseel, 2012) in R software (R Core Team, 2013). Like the RI-CLPM, the ALT-SR model allows to capture between-person starting levels (latent intercepts) which are interpreted as differences in people at the first time point (e.g. some adolescents use the smartphone more than others at T1). It also permits to differentiate within-person change over time in the autoregressive and cross-lagged paths. These changes are usually interpreted as the extent to which the amount of deviation above or below the person-specific mean in one variable (e.g., SU) at T1, is related to a successive deviation from the person-specific mean in the other variable (e.g., SU for autoregressive, and PSU, for cross-lagged paths) at T2, considering autoregressive-effects (e.g., SU at T1). Finally, the ALT-SR model also allows capturing the between-person diversities in the development (latent slopes) of the variables, indicating the increase or decrease in one variable over time (rate of change). At between-person level, a positive correlation between the intercept and the slope reflects that individuals with higher starting points in one variable also show a more accentuated development over time. *Vice versa*, a negative correlation highlights that higher starting levels in one variable are associated with a decrease in the slope in the same or the other variable, as well as lower starting levels tend to display a larger slope (Beaujean, 2014). The ALT-SR model is very flexible because it can be expanded to include time-invariant covariates, such as gender and personality, like in the present study. These covariates are modelled as exogenous predictors (like in latent curve models), and they are included in the structural equations for the latent intercept and slope. Hence, they are interpreted as predictors of the latent growth parameters. The residuals represent all the remaining variance in the observed scores, representing intra-individual fluctuations in SU and PSU over time. A particular advantage of the ALT-SR model is that the mean structure of the repeated measures is modelled only by the latent curve factors (intercept and slope), i.e. *between*-person variability, whereas the covariance structure of the repeated measures is modelled as a function of both the latent curve factors and the structured residuals, i.e. *within*-person variability.

In our model, the observed, mean-centred scores in SU and PSU were regressed on the latent growth parameters, i.e. the intercept and the slope (the latter was set to be 0.00, 1.0, 2.0, and 3.0, to reflect the equal amount of time passed between the data collection time periods). In addition, the same observed scores were regressed on their own latent variables, with loadings constrained to 1 (for structured residuals). The variance structure of the observed variables was set to zero, whereas the variance of the latent variables was set free.

We started from a baseline, fully unconstrained model. Next,

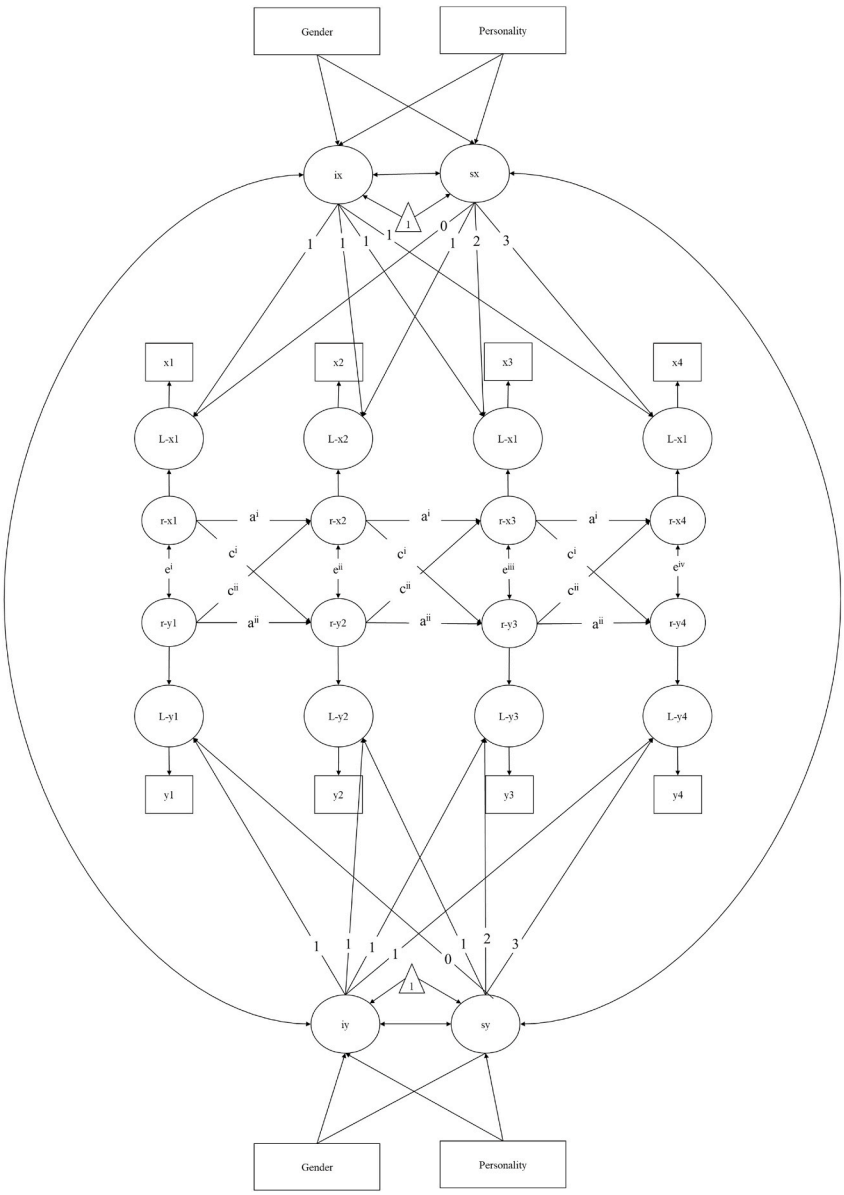

Fig. 1. ALT-SR model (Model 3). Legend: x1 = Smartphone Use at T1; x2 = Smartphone Use at T2; x3 = Smartphone Use at T3; x4 = Smartphone Use at T4; y1 = Problematic Smartphone Use at T1; y3 = Problematic Smartphone Use at T2; y3 = Problematic Smartphone Use at T3; y4 = Problematic Smartphone Use at T4; L = latent variable; r = residuals; I = intercept; s = slope; a^i = auto-regressive effects of Smartphone Use; a^{ii} = auto-regressive effects of Problematic Smartphone Use; c^i = cross-lagged effects from Smartphone Use to Problematic Smartphone Use; c^{ii} = cross-lagged effects from Problematic Smartphone Use to Smartphone Use; e = correlation between residuals. For personality, all dimensions were entered simultaneously in the model.

autoregressive, cross-lagged, and residual covariances were constrained to be equal across time in a series of subsequent nested models. At each step, the more parsimonious model was compared to the previous one using the χ^2 statistic, ΔCFI and ΔRMSEA, AIC, and BIC to detect a significant change in model fit. In addition, the BIC approximation of the Bayes factor (Hoijtink, Mulder, van Lissa, & Gu, 2019; Masson, 2011) was used to quantify how much more likely the hypothesized relationships in H1 can be observed (model with more constrains) compared to H0 (model with no/fewer constraints). Hence, for each model, a Bayes Factor [BF_{01} = exp ((BIC_0 – BIC_1)/2)] was calculated. According to Wagenmakers (2007), a BF_{01} in the range of 1–3, 3–20, 20–150, and >150 will be interpreted, respectively, as weak, positive, strong, and very strong evidence in favor of H1 (where H1 is the model with added constraints). The BF_{01} can then be converted to the posterior probability that the data favor the alternative hypothesis as follows: prH1 = $BF_{01}/(BF_{01}+1)$ and interpreted accordingly (Masson, 2011).

Once the appropriate model with respect to the invariance constraints was established, gender and, subsequently, personality traits, were added as time-invariant predictors of the intercepts and the slopes of SU and PSU. To evaluate the model fit, we inspected different fit goodness-of-indices, including the Comparative Fit Index (CFI), the Root Mean Square Error of Approximation (RMSEA), and the Standardized Root Mean Square Residual (SRMR). Given the large sample size for this study, the χ^2 value was not considered to be a good indicator of model fit. Byrne (2016)suggested to accept a model when the CFI is higher than 0.90 and close to 0.95, the RMSEA is 0.08 or less, and the SRMR is 0.05 or less. The main analyses are available in the https://osf.io/7s9pr/files/ repository.

7. Results

7.1. Preliminary results

Invariance testing of PSU showed that the scale remained invariant respect to gender, reaching a strict invariance at T1, T2, and T4, a weak invariance at T3, and a partial longitudinal invariance across the four waves (see Table 1 in Appendix A). Concerning sub-dimensions of personality, males reported higher levels of antagonism at T3 and T4, whereas females were higher in negative affectivity and psychoticism and both T3 and T4, and also in detachment at T3 (see Table 2 in Appendix A). These results highlight the importance to control for gender as a covariate in the ALT-SR model. Longitudinal results highlight that

personality levels remained stable for all the constructs over time, with the exception of antagonism and disinhibition, which tended to decrease one year later. In addition, paired-sample correlations were all positive and significant ($0.407 < r < 0.535$, $p < .001$), indicating that students tended to answer similarly to personality questions at both T3 and T4.

ICCs for SU (ICC = 0.320) and PSU (ICC = 0.370) indicate that around 32% and 37% of the variance in these variables were due to trait-like, between-person differences. In addition, the remaining 68% and 63% were respectively due to within-person fluctuations from one wave to the other. Hence, the use of the ALT-SR model is justified to disentangle the different sources of variability.

Bivariate correlation analysis (Table 1) revealed positive and significant relationships among the two studied concepts over the four measurement points. More precisely, levels of SU and PSU were positively related to each other within and across waves. They also showed an increment across time.

7.2. ALT-SR models

We tested three different ALT-SR models, the first without any covariates, the second with gender added as a covariate, and the third with gender and personality traits added as covariates. For parsimony, only the results of the third and final model will be reported hereafter. The results of the other two models are available in Appendix A (Tables 3–4 and Section 5).

After goodness-of-fit indices, AIC, BIC, and Bayes factors were inspected, our model building procedure pointed towards the model with autoregressive and cross-lagged paths constrained as equal across the four different time points as the best choice (see Table 2 for model fit comparisons). To respond to our focal research hypotheses, we entered the five personality sub-dimensions as covariates of intercepts and slopes in the model, together with gender ($\chi^2 = 92.963$, $df = 38$, $p = .000$, CFI = 0.974, RMSEA = 0.043, 90% CI [0.032, 0.054], SRMR = 0.026). Table 3 includes all coefficients of the full ALT-SR model with gender and personality traits added as covariates. At the within-person level, the cross-lagged effect from SU at T1, T2, T3 to PSU at T2, T3, T4 were all significant ($\beta = 0.070$, $p = .029$; $\beta = 0.101$, $p = .029$; $\beta = 0.114$, $p = .029$), indicating that adolescents' time spent on the smartphone increased PSU levels over time, beyond participants' typical levels in PSU, but this effect was not reciprocal. The correlations among the residuals at the within-person level were significant at T1, T2, and T3, but not at T4.

Controlling for personality, gender significantly predicted only the slope of PSU. In particular, females started with higher levels of PSU, and they tended to significantly decrease in their PSU levels at each wave compared to males ($B = -0.050$, $p = .043$). In addition, at the between-person level, the latent intercept of SU was significantly predicted by the personality traits of antagonism ($B = 0.444$, $p = .008$) and negative affectivity ($B = 0.289$, $p = .026$). In other words, the baseline level of SU ($\text{Intercept}_{SU} = .670$) was higher for adolescents reporting higher levels in these two traits. In a similar way, the latent intercept of PSU was significantly predicted by antagonism ($B = 0.288$, $p < .001$), negative affectivity ($B = 0.189$, $p = .001$), and, marginally, by detachment ($B = -0.138$, $p = .055$), indicating that adolescents with higher levels in these traits reported higher starting levels in PSU with respect to the baseline value ($\text{Intercept}_{PSU} = .886$). The intercepts of SU and PSU significantly correlated with each other ($r = 0.640$, $p < .001$)), indicating that adolescents who spent more time on the smartphone at T1 also reported higher levels of PSU at T1.

Personality was also a predictor of the slope of both SU and PSU. In particular, although the effect of gender remained marginally significant ($B = 0.100$, $p = .054$) in predicting the slope of SU, reflecting that females' increase was 0.619 and males of 0.519 over time, psychoticism was the other significant predictor ($B = 0.104$, $p = .035$). This indicates that young people higher in this trait were more inclined to use the smartphone more often over the years. At the same time, gender was still

Table 3
Final ALT-SR model estimates.

Model 3	Estimate/ Beta	SE.	[95% CI]	p-value	β
Between-person effects					
Correlations					
Corr ix-iy	.575	.073	[.432 - .718]	**.000**	
Corr sx-sy	.226	.178	[-.123 - .575]	.250	
Corr ix-sx	-.447	.075	[-.593 to −.301]	**.000**	
Corr ix-sy	-.258	.109	[-.472 to −.045]	**.018**	
Corr iy-sx	-.179	.110	[-.395 - .037]	.104	
Corr iy-sy	-.618	.065	[-.745 to −.492]	**.000**	
Intercepts					
ix	.670	.334	[.016–1.324]	.045	
iy	.886	.153	[.586–1.185]	.000	
sx	.519	.136	[.253 - .785]	.000	
sy	-.147	.067	[-.278 to −.016]	.028	
Covariates					
Gender (Female)→ ix	.049	.127	[-.200 - .298]	.701	.018
Antagonism– > ix	.444	.166	[.118 - .769]	**.008**	.144
Detachment– > ix	-.087	.153	[-.388 - .213]	.569	-.030
Disinhibition– > ix	.267	.142	[-.012 - .546]	.061	.098
Negative affect– > ix	.289	.130	[.034 - .543]	**.026**	.126
Psychoticism– > ix	-.138	.122	[-.377 - .101]	.258	-.064
Gender (Female)→ iy	.041	.056	[-.069 - .150]	.467	.035
Antagonism– > iy	.288	.077	[.137 - .439]	**.000**	.216
Detachment– > iy	-.138	.072	[-.278 - .003]	**.055**	-.108
Disinhibition– > iy	.114	.064	[-.012 - .239]	.075	.096
Negative affect– > iy	.189	.059	[.073 - .305]	**.001**	.190
Psychoticism– > iy	.054	.055	[-.053 - .161]	.321	.058
Gender (Female)→ sx	.100	.052	[-.002 - .201]	**.054**	.118
Antagonism– > sx	-.055	.067	[-.186 - .076]	.412	-.057
Detachment– > sx	-.074	.062	[-.196 - .047]	.230	-.800
Disinhibition– > sx	.059	.057	[-.053 - .170]	.304	.069
Negative affect– > sx	-.018	.054	[-.124 - .089]	.746	-.024
Psychoticism– > sx	.104	.049	[.007 - .201]	**.035**	.155
Gender (Female)→ sy	-.050	.024	[-.098 to −.002]	**.043**	-.124
Antagonism– > sy	.058	.032	[-.006 - .121]	.074	.126
Detachment– > sy	.051	.031	[-.010 - .112]	.100	.116
Disinhibition– > sy	.090	.028	[.036 - .144]	**.001**	.222
Negative affect– > sy	-.031	.024	[-.077 - .016]	.194	-.090
Psychoticism– > sy	-.015	.024	[-.062 - .033]	.194	-.090
Within-person effects					
Auto-regressive paths					
xT1→ x T2	.084	.061	[-.035 - .203]	.166	.058
xT2→ xT3	.084	.061	[-.035 - .203]	.166	.086
xT3→ xT4	.084	.061	[-.035 - .203]	.166	.101
yT1→ yT2	.018	.066	[-.110 - .147]	.783	.016
yT2→ yT3	.018	.066	[-.110 - .147]	.783	.018
yT3→ yT4	.018	.066	[-.110 - .147]	.783	.021
Cross-lagged paths					
xT1→ yT2	.045	.021	[.005 - .086]	**.029**	.070
xT2→ yT3	.045	.021	[.005 - .086]	**.029**	.101
xT3→ yT4	.045	.021	[.005 - .086]	**.029**	.114
yT1→ xT2	.048	.095	[-.138 - .235]	.612	.019
yT2→ xT3	.048	.095	[-.138 - .235]	.612	.022
yT3→ xT4	.048	.095	[-.138 - .235]	.612	.027
Residuals correlations					
Corr xT1-yT1	.351	.096	[.164 - .538]	**.000**	
Corr xT2-yT2	.406	.045	[.319 - .493]	**.000**	
Corr xT3-yT3	.280	.053	[.176 - .384]	**.000**	
Corr xT4-yT4	.141	.101	[-.057 - .338]	.162	

a significant predictor of the slope in PSU (B = −0.050, p = .043), indicating that females rate of change was −0.097 respect to males, for which it was −0.147, reflecting that PSU levels tend do decrease across time points, especially in males. Disinhibition had a significant impact on the slope of PSU (B = 0.090, p = .001). In addition, the intercept of SU was negatively correlated with the slope of SU (r = −0.471, p < .001) as well as the slope of PSU (r = −0.258, p = .018), indicating that higher levels of SU at T1 were associated with a lower increment in SU and PSU over time. *Viceversa*, adolescents who showed lower levels in SU at T1 tended to increase their SU and PSU over the years. In a similar way, the intercept of PSU was negatively correlated with the slope of the same variable (r = −0.618, p < .001). In other words, adolescents with higher levels of PSU at T1 showed a decrease of self-reported PSU over time. The correlation between the two slopes was not significant, indicating that the rate of change in SU was not related to the rate of change in PSU.

8. Discussion

According to international reports, both smartphone ownership and usage have increased steadily over the last years (Rideout & Robb, 2019; Süss et al., 2018, p. 83). According to the I-PACE model (Brand et al., 2016, 2019), the engagement in smartphone activities are initially driven by impulsive traits, which, together with problems in disinhibition, result in compulsive behaviors as one way to regulate negative emotions. However, the scientific literature has not yet tested these associations. There are the main research gaps to be filled: Firstly, no study to date has used the more comprehensive and recently developed DSM-5 model of personality to investigate which personality traits influence SU and PSU in adolescents. Secondly, there is still a lack of longitudinal research on SU and PSU that focus on the adolescent developmental period, especially research that allows to differentiate between and *within*- and *between*-person effects. Thirdly, to the best of our knowledge, no study to date has investigated the longitudinal relationships between SU and PSU that takes into account personality traits as predisposing factors that potentially influence the relationship longitudinal relationships between SU and PSU. To overcome these limits, the present study considered the development and interrelation of SU and PSU over time by using annual self-report data collected over the course of four years from 855 adolescents aged 11 at the first measurement point. Furthermore, it investigated how personality traits can influence the longitudinal and bidirectional relationships between SU and PSU in adolescence, using the ALT-SR model, which allows the inclusion of two random intercepts and slopes to separate *within*- and *between*-person level of change over time (Curran et al., 2014). This methodology offers a unique way through which developmental hypotheses can be tested.

At the *between*-person level, two personality traits were found to consistently and positively influence initial levels of SU and PSU, i.e. antagonism and negative affect. Antagonism, as part of the externalizing dimension of personality (Watson & Clark, 2020), involves having an exaggerated sense of the self, expectations of special treatment, as well as having little consideration for others' needs and feelings (Krueger & Markon, 2014). These features have been repeatedly related to narcissistic personality traits, especially grandiose narcissism, which includes arrogance, tendency to manipulate and subdue others, and insensitivity, in order to fulfil personal needs of approval and validation, and to boost self-esteem (Weiss, Campbell, Lynam, & Miller, 2019; Wright et al., 2013). Narcissism has been related to increased duration and frequency of social media activities (McCain & Campbell, 2018), since not only social media provide many possibilities to post contents and reach others (trait hypothesis), but also new opportunities to promote the self (self-enhancement hypothesis), and to obtain more yet weaker social ties (fit hypothesis). In addition, narcissistic traits have been reported to promote a problematic use of social media (Casale & Banchi, 2020), which are an ideal tool for exhibiting grandiosity and getting the desired attention. On social media platforms, users are in control of the image they want to convey and can get the desired rewards in the form of likes, comments, and followers. In addition, the ubiquity of social media, programmed to best fit access from mobile devices such as the smartphone, give adolescents with a high level of narcissism the possibility to have access to that kind of reward anytime and anywhere throughout the day. This possibility constitutes a risk factor for an increasead compulsive use of social media sites. Hence, it is not surprising that, in the present study, adolescents with higher levels of antagonism also spent more time on the smartphone and reported higher levels of PSU over time.

In addition, the personality trait of negative affect showed to influence initial levels of both SU and PSU in adolescents. Previous studies demonstrated that negative affect, part of the internalizing dimension of personality (Watson & Clark, 2020), is a crucial component of addictive behaviors (Di Nicola et al., 2010; Presta et al., 2002), especially in the initial and maintaining phases of addictions (Kassel et al., 2007). Negative affect is closely related to neuroticism, which is part of the better known Big Five model of personality traits (Gore & Widiger, 2013). Neurotic people experience frequent and intense negative emotions such as anxiety, depression, and worrisome. They tend to report more daily problems, show stronger emotional reactions, and exaggerated reactivity to stressors (Suls & Martin, 2005). In a meta-analysis of 159 studies on (problematic) online activities, Marciano et al. (2020) found that high levels of neuroticism significantly correlate with all measures of problematic online behaviors, including PSU. In the present study, PSU, but also non-problematic SU, can be a considered a coping tool to deal with the urgency of negative emotions, and a way to escape from them. Furthermore, people with high levels of neuroticism tend to use the Internet, accessed through the smartphone, to hide their shyness and fears caused by offline social settings, and to avoid the manifestation of social anxiety and negative emotional reactions caused by others' opinions in face-to-face interactions (Marriott & Buchanan, 2014). However, the link between negative affect and PSU is more complex, since measures of PSU already involve the assessment of symptoms experienced by a person reporting high levels in this trait (for a detailed discussion see Marciano et al., 2020).

Another interesting finding of the present study is that levels of SU were found to augment more over time (i.e., increased slope) in people with higher levels of psychoticism. Psychotic adolescents tend to experience dissociation states and show unusual perceptions and beliefs of the reality (Arango, 2011; Schultze-Lutter, Michel, Ruhrmann, & Schimmelmann, 2014). That said, the Internet allows adolescents with higher levels of psychoticism to express different states of the self, which cannot be shown in the real world due to embarrassment or disapproval. Indeed, the Internet can be seen as a "transition space" (Eichenberg, Huss, & Küsel, 2017), where illusion meets reality, leaving space for playful and imaginary experiences, during which fantasies can be expressed (Rosegrant, 2012).

Eventually, disinhibition significantly contributed to an increment (i.e., increased slope) in PSU over time. Adolescents with high levels of disinhibition are more likely to lose self-control and are, thus, more propense to compulsive behaviors (Grant et al., 2006; Stein et al., 1994), which contribute to a stronger dependence on the smartphone, also fostered by the easy portability and accessibility of the device. This result is in line with the literature on behavioral addictions, pointing at disinhibition as the personality trait that triggers the switch from impulsive to compulsive behavioral patterns (Brand et al., 2016, 2019). As in substance-use disorders, impulsive traits are pivotal features in starting a specific behavior, which develops compulsive features afterwards (Dell'Osso et al., 2006). The exposure to behavioral rewards, like the ones obtained through repeated smartphone use, can induce changes in brain areas which are similar to the ones reported in substance-related addictions (He, Turel, & Bechara, 2017; Olsen, 2011). From a neurobiological point of view, frequent SU depends on lower efficiency of neural systems related to impulsivity, like the prefrontal cortex, which fails in inhibiting the control over urges (Ioannidis et al., 2019). The frontostriatal dysfunction, as described in the context of other addictive

behaviors, promotes a compulsive use of the smartphone and the development of PSU (Feil et al., 2010; Lüscher, Robbins, & Everitt, 2020). Interestingly, the relationships between affective and cognitive states, and the decision to use the smartphone, have been reported to be moderated by inhibitory control (Hahn, Reuter, Spinath, & Montag, 2017), particularly in its early stages. After that, specific behaviors (like social media use) may provide gratification and relief from negative moods (Laier & Brand, 2017; Laier et al., 2018), and, thus, create specific reward expectancies and contribute to modifications in users' individual coping style.

To conclude our discussion on the role of personality traits in the bidirectional effects of SU and PSU, we can say that antagonism and disinhibition, two traits included in the externalizing dimension of personality, decline with age. This result is in line with studies focusing on the cascading effects of externalizing problems, which lead to higher internalizing and academic problems in later years (Moilanen, Shaw, & Maxwell, 2010). In addition, this result is in line with neuroscientific studies on adolescent brain development, reporting that as brain and neural connections develop, externalizing symptoms decrease (Andre, Geeraert, & Lebel, 2020). However, this result should be replicated in further research investigating how personality traits, ideally assessed through the novel DSM-5 model, develop over time.

Besides our particular interest in the role of personality traits in the longitudinal relationship between SU and PSU in adolescence, the present study investigated the intra-individual relationships between SU and PSU over the course of four years. In doing so, it responds to recent calls for the study on the causality relationships between smartphone use and dysfunctions on this use (Harris, Regan, Schueler, & Fields, 2020). More precisely, at the *within*-person level, we found that increased daily SU led to higher levels of self-reported PSU all over all four measurement points. This result confirms findings from previous studies on the relationship between duration of device use and problematic use both in the context of both smartphone (Haug et al., 2015b) and Internet use (Ko et al., 2014). Adolescents in middle schools, the age group considered in this study, focus their attention on building and maintaining peer relationships (Nickerson & Nagle, 2005), mainly through instant messaging as a specific form of social networking (Valkenburg & Peter, 2007). The enlargement of the social sphere and the onset of puberty make adolescents, and girls in particular, more preoccupied and worried about their social standing (McElhaney, Antonishak, & Allen, 2008). This goes along with the fact that, compared to boys, girls show higher interpersonal dependence, more self-image and self-esteem concerns, and a higher need for external approval and success (Weller, Kloos, Kang, & Weller, 2006). These characteristics promote a compulsive use of the smartphone to maintain and increase their personal social standing. In fact, in the present study, we found that being female was marginally associated with increased slopes in both SU and PSU over time. This finding is in line with prior research highlighting that girls are more active on social networking sites (Waller, Willemse, Genner, Suter, & Süss, 2016) and at higher risk of smartphone addiction (Pereira, Bevilacqua, Coimbra, & Andrade, 2020). In other words, girls seem to experience addictive symptoms more quickly and show higher vulnerability towards the excessive use of digital technologies.

At the *between*-person level, the positive correlation between SU and PSU reflects that adolescents who reported higher levels in SU also showed higher levels of PSU this finding is in line with previous findings from cross-sectional studies (Kwon et al., 2013; Ryding & Kuss, 2020), yet this study went further by investigating the intraindividual reciprocal relationships between the two. In addition, higher levels of SU were associated with a lower increment in SU and PSU over time, which points towards a saturation effect, whereas adolescents who showed more moderate levels in SU at the beginning tended to increase their SU and PSU levels more strongly over the years. At the same time, adolescents with higher levels of PSU tended to report similar, or lower, levels of PSU over time, whereas people with lower rates at the first measurement point reported a higher increment over the following years.

8.1. Limitations and future directions

Some methodological limitations of the present study should be acknowledged. First, given the topical variety of the larger longitudinal study from which the data were taken, we used only two-item indicators to measure overall daily duration of SU. Although single time estimates have been found to correlate with objective SU more than multi-item scales (Ellis, Davidson, Shaw, & Geyer, 2019), a more detailed assessment with multi-item indicators covering different types of SU, e.g., social media use, online gaming, use of instant messaging apps, would provide further insights on the hypothesized bidirectional relationships investigated in this study. That said, it would also be beneficial to introduce Ecological Momentary Assessments of SU, as the use of multiple short surveys throughout a day would provide an even more detailed and reliable picture of within-person experiences and bidirectional effects of the concepts investigated in this study. This is particularly relevant, considering that self-report use was found to correlate with objectively measured use only to a small-to-moderate degree (Ellis et al., 2019), also in adolescents (Marciano & Camerini, 2020). However, none of the measures of SU (traditional self-report, EMAs, trace data) presents a "gold standard" to date and each implies its own challenges and biases (see also chapter 2.3). Thus, future conceptual and methodological research is needed to better guide researchers in the choice of the measure of SU for their study purposes. In addition, PSU could be measured with more specific tools (e.g. using smartphone apps allowing to collect objective trace data), aiming to investigate to which particular activity adolescents are addicted to. Another limitation of the present study is that participants in the analytical sample reported lower levels of PSU compared to dropped cases. Biased drop-outs in studies with youth have been reported previously (e.g., Wolke, Waylen, Samara, Steer, Goodman, Ford & Lamberts, 2009). Hence, future studies should consider alternative strategy to obtain unbiased estimates with missing measures, such as the Heckman-type selection (Koné, Bonfoh, Dao, Koné, & Fink, 2019). Furthermore, personality was only measured at two-time points, hence, future research should assess personality traits for a longer time, to better capture trait fluctuations during the developmental period of adolescence. The consideration of additional predisposing factors, such as narcissism, empathy, introversion, or trait anxiety, would also add more insights to the study of the effects of SU on PSU. Interestingly, considering repeated measures design using both EMAs and trace data together with the measurement of covariates, and modelling them using longitudinal methods such as latent growth curve analysis (e.g., Rozgonjuk, Levine, Hall, & Elhai, 2018) would also give additional insight into the correlates of PSU in adolescence. The present study lays the grounds for different directions for future research. First, future research should also be based on longitudinal data with at least three or four waves, which allow disentangling *within*- and *between*--person effects to replicate the findings of this study. Third and last. Eventually, future studies using advanced statistical models, such as the ALT-SR model or the RI-CLPM (Hamaker et al., 2015), should include biological and bio-behavioral data as covariates, e.g., cognitive or brain-related measures (e.g., Kühn et al., 2020). The integration of such measures would enrich our understanding of the biological predispositions (and changes during adolescence) that affect SU and PSU in this critical developmental period.

Credit author statement

Laura Marciano: Conceptualization, Methodology, Software, Formal analysis, Writing – original draft, Writing – review & editing, Visualization. Peter J. Schulz: Conceptualization, Writing – review & editing, Supervision. Anne-Linda Camerini: Resources, Writing – review & editing, Supervision, Project administration, Funding acquisition.

Data statement

The dataset generated during and during the current study and the main analyses are available in the https://osf.io/7s9pr/files/repository.

Declaration of competing interest

None.

Acknowledgements

This work was supported by the Swiss National Science Foundation, (SNSF) [10001C_175874].

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chb.2021.106731.

Legend: x = Smartphone Use, y = Problematic Smartphone Use; corr = Pearson's correlation coefficient; i = latent intercept; s = latent slope.

Headings

- This paper sheds light on the longitudinal relation between smartphone and problematic smartphone use over four years.
- This study modelled data from 855 adolescents using an ALT-SR model, with gender and personality traits as covariates.
- SU significantly increased PSU at all four time points, but not *viceversa.*
- Antagonism and negative affect predicted the latent intercepts, whereas psychoticism and dishibition influencedthe latent slopes.

References

kita, E., & Luria, G. (2018). The mediating role of smartphone addiction on the relationship between personality and young drivers' smartphone use while driving. *Transportation Research Part F: Traffic Psychology and Behaviour, 59*(Part A), 203–211. https://doi.org/10.1016/j.trf.2018.09.001

Aboujaoude, E. (2017). The Internet's effect on personality traits: An important casualty of the 'Internet addiction' paradigm. *Journal of Behavioral Addictions, 6*(1), 1–4. https://doi.org/10.1556/2006.6.2017.009

Albert, D., Chein, J., & Steinberg, L. (2013). The teenage brain: Peer influences on adolescent decision making. *Current Directions in Psychological Science, 22*(2), 114–120. https://doi.org/10.1177/0963721412471347

M. F. Aljomaa, S. S., Qudah, Al, Albursan, I. S., Bakhiet, S. F., & Abduljabbar, A. S. (2016). Smartphone addiction among university students in the light of some variables *Computers in Human Behavior, 61*, 155–164. https://doi.org/10.1016/j.chb.2016.03.041

Allaby, M., & Shannon, C. S. (2020). "I just want to keep in touch": Adolescents' experiences with leisure-related smartphone use. *Journal of Leisure Research, 51*(3), 245–263. https://doi.org/10.1080/00222216.2019.1672506

American Psychiatric Association. (2013). In *Diagnostic and statistical manual of mental disorders: DSM-5* (5th ed.). American Psychiatric Association.

Andre, Q. R., Geeraert, B. L., & Lebel, C. (2020). Brain structure and internalizing and externalizing behavior in typically developing children and adolescents. *Brain Structure and Function, 225*(4), 1369–1378. https://doi.org/10.1007/s00429-019-01973-y

Arango, C. (2011). Attenuated psychotic symptoms syndrome: How it may affect child and adolescent psychiatry. *European Child & Adolescent Psychiatry, 20*(2), 67–70. https://doi.org/10.1007/s00787-010-0144-2

Beaujean, A. A. (2014). *Latent variable modeling using R: A step-by-step guide*. Routledge.

Beyens, I., Pouwels, J. L., Driel, I., Keijsers, L., & Valkenburg, P. (2020). *Social media use and adolescents' well-being: Developing a typology of person-specific effect patterns*. https://doi.org/10.31234/osf.io/ftygp

Beyens, I., Pouwels, J. L., van Driel, I. I., Keijsers, L., & Valkenburg, P. M. (2020). The effect of social media on well-being differs from adolescent to adolescent. *Scientific Reports, 10*(1), 10763. https://doi.org/10.1038/s41598-020-67727-7

Billieux, J., Maurage, P., Lopez-Fernandez, O., Kuss, D. J., & Griffiths, M. D. (2015). Can disordered mobile phone use Be considered a behavioral addiction? An update on current evidence and a comprehensive model for future research. *Current Addiction Reports, 2*(2), 156–162. https://doi.org/10.1007/s40429-015-0054-y

Billieux, J., Schimmenti, A., Khazaal, Y., Maurage, P., & Heeren, A. (2015). Are we overpathologizing everyday life? A tenable blueprint for behavioral addiction research. *Journal of Behavioral Addictions, 4*(3), 119–123. https://doi.org/10.1556/2006.4.2015.009

Block, J. J. (2008). Issues for DSM-V: Internet addiction. *American Journal of Psychiatry, 165*(3), 306–307.

Boase, J., & Ling, R. (2013). Measuring mobile phone use: Self-report versus log data. *Journal of Computer-Mediated Communication, 18*(4), 508–519. https://doi.org/10.1111/jcc4.12021

Bollen, K. A., & Long, J. S. (1993). *Testing structural equation models*. SAGE.

Bragazzi, N. L., & Del Puente, G. (2014). A proposal for including nomophobia in the new DSM-V. *Psychology Research and Behavior Management, 7*, 155–160. https://doi.org/10.2147/PRBM.S41386

Brand, M., Wegmann, E., Stark, R., Müller, A., Wölfling, K., Robbins, T. W., et al. (2019). The interaction of person-affect-cognition-execution (I-PACE) model for addictive behaviors: Update, generalization to addictive behaviors beyond internet-use disorders, and specification of the process character of addictive behaviors. *Neuroscience & Biobehavioral Reviews, 104*, 1–10. https://doi.org/10.1016/j.neubiorev.2019.06.032

Brand, M., Young, K. S., Laier, C., Wölfling, K., & Potenza, M. N. (2016). Integrating psychological and neurobiological considerations regarding the development and maintenance of specific Internet-use disorders: An Interaction of Person-Affect-Cognition-Execution (I-PACE) model. *Neuroscience & Biobehavioral Reviews, 71*, 252–266. https://doi.org/10.1016/j.neubiorev.2016.08.033

Brewer, J. A., & Potenza, M. N. (2008). The neurobiology and genetics of impulse control disorders: Relationships to drug addictions. *Biochemical Pharmacology, 75*(1), 63–75. https://doi.org/10.1016/j.bcp.2007.06.043

Burnett, S., Sebastian, C., Cohen Kadosh, K., & Blakemore, S.-J. (2011). The social brain in adolescence: Evidence from functional magnetic resonance imaging and behavioural studies. *Neuroscience & Biobehavioral Reviews, 35*(8), 1654–1664. https://doi.org/10.1016/j.neubiorev.2010.10.011

Byrne, B. M. (2016). *Structural equation modeling with AMOS: Basic concepts, applications, and programming* (3rd ed.). Routledge. https://doi.org/10.4324/9781315757421

Byrne, B. M., Shavelson, R. J., & Muthén, B. (1989). Testing for the equivalence of factor covariance and mean structures: The issue of partial measurement invariance. *Psychological Bulletin, 105*(3), 456–466. https://doi.org/10.1037/0033-2909.105.3.456

Camerini, A.-L., Gerosa, T., & Marciano, L. (2020). *Predicting problematic smartphone use over time in adolescence: A latent class regression analysis of online and offline activities*. New Media & Society. https://doi.org/10.1177/1461444820948809

Camerini, A. L., & Marciano, L. (2019, May 24). The longitudinal relationship between smartphone use, smartphone addiction and depression in adolescents: An application of the RI-CLPM. In *69th annual conference of the international communication association (ICA), Washington DC, United States*.

Camerini, A. L., Schulz, P. J., & Jeannet, A. M. (2018). The social inequalities of Internet access, its use, and the impact on children's academic performance: Evidence from a longitudinal study in Switzerland. *New Media & Society, 20*(7), 2489–2508.

Carvalho, L. F., Sette, C. P., & Ferrari, B. L. (2018). Problematic smartphone use relationship with pathological personality traits: Systematic review and meta-analysis. *Cyberpsychology: Journal of Psychosocial Research on Cyberspace, 12*(3). https://doi.org/10.5817/CP2018-3-5. Article 3.

Casale, S., & Banchi, V. (2020). Narcissism and problematic social media use: A systematic literature review. *Addictive Behaviors Reports, 11*, 100252. https://doi.org/10.1016/j.abrep.2020.100252

Chen, F. F. (2007). Sensitivity of goodness of fit indexes to lack of measurement invariance. *Structural Equation Modeling: A Multidisciplinary Journal, 14*(3), 464–504. https://doi.org/10.1080/10705510701301834

Cheung, G. W., & Rensvold, R. B. (2002). Evaluating goodness-of-fit indexes for testing measurement invariance. *Structural Equation Modeling: A Multidisciplinary Journal, 9*(2), 233–255. https://doi.org/10.1207/S15328007SEM0902_5

Chin, F., & Leung, C. H. (2018). The concurrent validity of the internet addiction test (IAT) and the mobile phone dependence questionnaire (MPDQ). *PloS One, 13*(6), Article e0197562. https://doi.org/10.1371/journal.pone.0197562

Cho, K.-S., & Lee, J.-M. (2017). Influence of smartphone addiction proneness of young children on problematic behaviors and emotional intelligence: Mediating self-assessment effects of parents using smartphones. *Computers in Human Behavior, 66*, 303–311. https://doi.org/10.1016/j.chb.2016.09.063. psyh.

Chotpitayasunondh, V., & Douglas, K. M. (2016). How "phubbing" becomes the norm: The antecedents and consequences of snubbing via smartphone. *Computers in Human Behavior, 63*, 9–18. https://doi.org/10.1016/j.chb.2016.05.018

Ciccarelli, M., Nigro, G., Griffiths, M. D., D'Olimpio, F., & Cosenza, M. (2020). The associations between maladaptive personality traits, craving, alcohol use, and adolescent problem gambling: An Italian survey study. *Journal of Gambling Studies, 36*(1), 243–258. https://doi.org/10.1007/s10899-019-09872-x

Cohen, P. (2008). Child development and personality disorder. *Psychiatric Clinics of North America, 31*(3), 477–493. https://doi.org/10.1016/j.psc.2008.03.005

Cooley, C. H. (1902). Looking-glass self. In *Looking-glass self. The production of reality: Essays and readings on social interaction* (Vol. 6).

Costello, E. J., Copeland, W., & Angold, A. (2011). Trends in psychopathology across the adolescent years: What changes when children become adolescents, and when adolescents become adults? *The Journal of Child Psychology and Psychiatry and Allied Disciplines, 52*(10), 1015–1025. https://doi.org/10.1111/j.1469-7610.2011.02446.x

Coyne, S. M., Rogers, A. A., Zurcher, J. D., Stockdale, L., & Booth, M. (2020). Does time spent using social media impact mental health?: An eight year longitudinal study. *Computers in Human Behavior, 104*, 106160. https://doi.org/10.1016/j.chb.2019.106160

Crone, E. A., & Konijn, E. A. (2018). Media use and brain development during adolescence. *Nature Communications, 9*(1), 588. https://doi.org/10.1038/s41467-018-03126-x

Curran, P. J., Howard, A. L., Bainter, S. A., Lane, S. T., & McGinley, J. S. (2014). The separation of between-person and within-person components of individual change over time: A latent curve model with structured residuals. *Journal of Consulting and Clinical Psychology, 82*(5), 879–894. https://doi.org/10.1037/a0035297

Cuzen, N. L., & Stein, D. J. (2014). Chapter 2 - behavioral addiction: The nexus of impulsivity and compulsivity. In K. P. R.&L. C. Feder (Ed.), *Behavioral addictions* (pp. 19–34). Academic Press. https://doi.org/10.1016/B978-0-12-407724-9.00002-1.

Davis, J. P., Pedersen, E. R., Tucker, J. S., Dunbar, M. S., Seelam, R., Shih, R., et al. (2019a). Long-term associations between substance use-related media exposure, descriptive norms, and alcohol use from adolescence to young adulthood. *Journal of Youth and Adolescence, 48*(7), 1311–1326. https://doi.org/10.1007/s10964-019-01024-z

De-Sola Gutiérrez, J., Rodríguez de Fonseca, F., & Rubio, G. (2016). Cell-phone addiction: A review. *Frontiers in Psychiatry, 7*. https://doi.org/10.3389/fpsyt.2016.00175

Dell'Osso, B., Altamura, A. C., Allen, A., Marazziti, D., & Hollander, E. (2006). Epidemiologic and clinical updates on impulse control disorders: A critical review. *European Archives of Psychiatry and Clinical Neuroscience, 256*(8), 464–475. https://doi.org/10.1007/s00406-006-0668-0

Di Nicola, M., Tedeschi, D., Mazza, M., Martinotti, G., Harnic, D., Catalano, V., et al. (2010). Behavioural addictions in bipolar disorder patients: Role of impulsivity and personality dimensions. *Journal of Affective Disorders, 125*(1), 82–88. https://doi.org/10.1016/j.jad.2009.12.016

Domoff, S. E., Foley, R. P., & Ferkel, R. (2020). Addictive phone use and academic performance in adolescents. *Human Behavior and Emerging Technologies, 2*(1), 33–38. https://doi.org/10.1002/hbe2.171

Duke, É., & Montag, C. (2017). Smartphone addiction, daily interruptions and self-reported productivity. *Addictive Behaviors Reports, 6*, 90–95. https://doi.org/10.1016/j.abrep.2017.07.002

Dunbar, M. S., Davis, J. P., Rodriguez, A., Tucker, J. S., Seelam, R., & D'Amico, E. J. (2019). Disentangling within- and between-person effects of shared risk factors on E-cigarette and cigarette use trajectories from late adolescence to young adulthood. *Nicotine & Tobacco Research, 21*(10), 1414–1422. https://doi.org/10.1093/ntr/nty179

Eichenberg, C., Huss, J., & Küsel, C. (2017). From online dating to online divorce: An overview of couple and family relationships shaped through digital media. *Contemporary Family Therapy, 39*(4), 249–260. https://doi.org/10.1007/s10591-017-9434-x

Elhai, J. D., Dvorak, R. D., Levine, J. C., & Hall, B. J. (2017). Problematic smartphone use: A conceptual overview and systematic review of relations with anxiety and depression psychopathology. *Journal of Affective Disorders, 207*, 251–259. https://doi.org/10.1016/j.jad.2016.08.030

Elhai, J. D., Levine, J. C., Alghraibeh, A. M., Alafnan, A. A., Aldraiweesh, A. A., & Hall, B. J. (2018). Fear of missing out: Testing relationships with negative affectivity, online social engagement, and problematic smartphone use. *Computers in Human Behavior, 89*, 289–298. https://doi.org/10.1016/j.chb.2018.08.020

Elhai, J. D., Levine, J. C., Dvorak, R. D., & Hall, B. J. (2016). Fear of missing out, need for touch, anxiety and depression are related to problematic smartphone use. *Computers in Human Behavior, 63*, 509–516. https://doi.org/10.1016/j.chb.2016.05.079

Elhai, J. D., Levine, J. C., & Hall, B. J. (2019). The relationship between anxiety symptom severity and problematic smartphone use: A review of the literature and conceptual frameworks. *Journal of Anxiety Disorders, 62*, 45–52. https://doi.org/10.1016/j.janxdis.2018.11.005

Elhai, J. D., Rozgonjuk, D., Alghraibeh, A. M., Levine, J. C., Alafnan, A. A., Aldraiweesh, A. A., et al. (2020). Excessive reassurance seeking mediates relations between rumination and problematic smartphone use. *Bulletin of the Menninger Clinic, 84*(2), 137–155. https://doi.org/10.1521/bumc_2020_84_07

Elhai, J. D., Tiamiyu, M. F., Weeks, J. W., Levine, J. C., Picard, K. J., & Hall, B. J. (2018). Depression and emotion regulation predict objective smartphone use measured over one week. *Personality and Individual Differences, 133*, 21–28. https://doi.org/10.1016/j.paid.2017.04.051

Elhai, J. D., Yang, H., & Montag, C. (2020). Fear of missing out (FOMO): Overview, theoretical underpinnings, and literature review on relations with severity of negative affectivity and problematic technology use. *Brazilian Journal of Psychiatry*. https://doi.org/10.1590/1516-4446-2020-0870

Elhai, J. D., Yang, H., Rozgonjuk, D., & Montag, C. (2020). Using machine learning to model problematic smartphone use severity: The significant role of fear of missing out. *Addictive Behaviors, 103*, 106261. https://doi.org/10.1016/j.addbeh.2019.106261

Ellis, D. A. (2019). Are smartphones really that bad? Improving the psychological measurement of technology-related behaviors. *Computers in Human Behavior, 97*, 60–66. https://doi.org/10.1016/j.chb.2019.03.006

Ellis, D. A., Davidson, B. I., Shaw, H., & Geyer, K. (2019). Do smartphone usage scales predict behavior? *International Journal of Human-Computer Studies, 130*, 86–92. https://doi.org/10.1016/j.ijhcs.2019.05.004

Feil, J., Sheppard, D., Fitzgerald, P. B., Yücel, M., Lubman, D. I., & Bradshaw, J. L. (2010). Addiction, compulsive drug seeking, and the role of frontostriatal mechanisms in regulating inhibitory control. *Neuroscience & Biobehavioral Reviews, 35*(2), 248–275. https://doi.org/10.1016/j.neubiorev.2010.03.001

Fernandez, D. P., Kuss, D. J., & Griffiths, M. D. (2020). Short-term abstinence effects across potential behavioral addictions: A systematic review. *Clinical Psychology Review, 76*. https://doi.org/10.1016/j.cpr.2020.101828

Flynn, E., Thériault, É., & Williams, S. (2020). The use of smartphones to cope with stress in university students: Helpful or harmful? *Journal of Technology in Behavioral Science, 5*. https://doi.org/10.1007/s41347-019-00125-7

Fossati, A., Somma, A., Borroni, S., Markon, K. E., & Krueger, R. F. (2017). The personality inventory for DSM-5 brief form: Evidence for reliability and construct validity in a sample of community-dwelling Italian adolescents. *Assessment, 24*(5), 615–631. https://doi.org/10.1177/1073191115621793

Fu, L., Wang, P., Zhao, M., Xie, X., Chen, Y., Nie, J., et al. (2020). Can emotion regulation difficulty lead to adolescent problematic smartphone use? A moderated mediation model of depression and perceived social support. *Children and Youth Services Review, 108*, 104660. https://doi.org/10.1016/j.childyouth.2019.104660

Galván, A. (2013). The teenage brain: Sensitivity to rewards. *Current Directions in Psychological Science, 22*(2), 88–93. https://doi.org/10.1177/0963721413480859

Gervasi, A. M., La Marca, L., Lombardo, E., Mannino, G., Iacolino, C., & Schimmenti, A. (2017). Maladaptive personality traits and internet addiction symptoms among young adults: A study based on the alternative DSM-5 model for personality disorders. *Clinical neuropsychiatry, 14*(1).

Gökçearslan, Ş., Mumcu, F. K., Haşlaman, T., & Çevik, Y. D. (2016). Modelling smartphone addiction: The role of smartphone usage, self-regulation, general self-efficacy and cyberloafing in university students. *Computers in Human Behavior, 63*, 639–649. https://doi.org/10.1016/j.chb.2016.05.091

Gore, W. L., & Widiger, T. A. (2013). The DSM-5 dimensional trait model and five-factor models of general personality. *Journal of Abnormal Psychology, 122*(3), 816–821. https://doi.org/10.1037/a0032822

Grant, J. E., Brewer, J. A., & Potenza, M. N. (2006). The neurobiology of substance and behavioral addictions. *CNS Spectrums, 11*(12), 924–930. https://doi.org/10.1017/S109285290001511X

Griffiths, M. (1996). Gambling on the internet: A brief note. *Journal of Gambling Studies, 12*(4), 471–473. https://doi.org/10.1007/BF01539190

Hahn, E., Reuter, M., Spinath, F. M., & Montag, C. (2017). Internet addiction and its facets: The role of genetics and the relation to self-directedness. *Addictive Behaviors, 65*, 137–146. https://doi.org/10.1016/j.addbeh.2016.10.018

Haidt, J., & Allen, N. (2020). Scrutinizing the effects of digital technology on mental health. *Nature, 578*(7794), 226–227. https://doi.org/10.1038/d41586-020-00296-x

Hale, L., & Guan, S. (2015). Screen time and sleep among school-aged children and adolescents: A systematic literature review. *Sleep Medicine Reviews, 21*, 50–58. https://doi.org/10.1016/j.smrv.2014.07.007

Halfmann, A., & Rieger, D. (2019). Permanently on call: The effects of social pressure on smartphone users' self-control, need satisfaction, and well-being. *Journal of Computer-Mediated Communication, 24*(4), 165–181. https://doi.org/10.1093/jcmc/zmz008

Hamaker, E. L., Kuiper, R. M., & Grasman, R. P. P. P. (2015). A critique of the cross-lagged panel model. *Psychological Methods, 20*(1), 102–116. https://doi.org/10.1037/a0038889

Harris, B., Regan, T., Schueler, J., & Fields, S. A. (2020). Problematic mobile phone and smartphone use scales: A systematic review. *Frontiers in Psychology, 11*. https://doi.org/10.3389/fpsyg.2020.00672

Hartanto, A., & Yang, H. (2016). Is the smartphone a smart choice? The effect of smartphone separation on executive functions. *Computers in Human Behavior, 64*, 329–336. https://doi.org/10.1016/j.chb.2016.07.002

Haug, S., Castro, R. P., Kwon, M., Filler, A., Kowatsch, T., & Schaub, M. P. (2015a). Smartphone use and smartphone addiction among young people in Switzerland. *Journal of Behavioral Addictions, 4*(4), 299–307. https://doi.org/10.1556/2006.4.2015.037

Haug, S., Castro, R. P., Kwon, M., Filler, A., Kowatsch, T., & Schaub, M. P. (2015b). Smartphone use and smartphone addiction among young people in Switzerland. *Journal of Behavioral Addictions, 4*(4), 299–307. https://doi.org/10.1556/2006.4.2015.037

Heron, K. E., Everhart, R. S., McHale, S. M., & Smyth, J. M. (2017). Using mobile-technology-based ecological momentary assessment (EMA) methods with youth: A systematic review and recommendations. *Journal of Pediatric Psychology, 42*(10), 1087–1107. https://doi.org/10.1093/jpepsy/jsx078

He, Q., Turel, O., & Bechara, A. (2017). Brain anatomy alterations associated with Social Networking Site (SNS) addiction. *Scientific Reports, 7*(1), 45064. https://doi.org/10.1038/srep45064

Hirschfeld, G., & Brachel, R. von (2014). *Improving Multiple-Group confirmatory factor analysis in R – A tutorial in measurement invariance with continuous and ordinal indicators*. https://doi.org/10.7275/QAZY-2946

Hoijtink, H., Mulder, J., van Lissa, C., & Gu, X. (2019). A tutorial on testing hypotheses using the Bayes factor. *Psychological Methods, 24*(5), 539–556. https://doi.org/10.1037/met0000201

Ioannidis, K., Hook, R., Goudriaan, A. E., Vlies, S., Fineberg, N. A., Grant, J. E., et al. (2019). Cognitive deficits in problematic internet use: Meta-analysis of 40 studies. *British Journal of Psychiatry, 215*(5), 639–646 (pbh).

Jo, Y. S., Bhang, S. Y., Choi, J. S., Lee, H. K., Lee, S. Y., & Kweon, Y.-S. (2019). Clinical characteristics of diagnosis for internet gaming disorder: Comparison of DSM-5 IGD and ICD-11 GD diagnosis. *Journal of Clinical Medicine, 8*(7). https://doi.org/10.3390/jcm8070945

Kassel, J. D., Veilleux, J. C., Wardle, M. C., Yates, M. C., Greenstein, J. E., Evatt, D. P., et al. (2007). Negative affect and addiction. In M. Al'Absi (Ed.), *Stress and addiction: Biological and psychological mechanisms* (pp. 171–189). Academic Press.

Kayiş, A. R., Satici, S. A., Yilmaz, M. F., Şimşek, D., Ceyhan, E., & Bakioğlu, F. (2016). Big five-personality trait and internet addiction: A meta-analytic review. *Computers in Human Behavior, 63*, 35–40. https://doi.org/10.1016/j.chb.2016.05.012

Kobayashi, T., & Boase, J. (2012). No such effect? The implications of measurement error in self-report measures of mobile communication use. *Communication Methods and Measures, 6*(2), 126–143. https://doi.org/10.1080/19312458.2012.679243

Ko, C.-H., Liu, T.-L., Wang, P.-W., Chen, C.-S., Yen, C.-F., & Yen, J.-Y. (2014). The exacerbation of depression, hostility, and social anxiety in the course of internet addiction among adolescents: A prospective study. *Comprehensive Psychiatry, 55*(6), 1377–1384. https://doi.org/10.1016/j.comppsych.2014.05.003

Koné, S., Bonfoh, B., Dao, D., Koné, I., & Fink, G. (2019). Heckman-type selection models to obtain unbiased estimates with missing measures outcome: Theoretical considerations and an application to missing birth weight data. *BMC Medical Research Methodology, 19*(1), 231. https://doi.org/10.1186/s12874-019-0840-7

Krueger, R. F., & Markon, K. E. (2014). The role of the DSM-5 personality trait model in moving toward a quantitative and empirically based approach to classifying personality and psychopathology. *Annual Review of Clinical Psychology, 10*(1), 477–501. https://doi.org/10.1146/annurev-clinpsy-032813-153732

Krumpal, I. (2013). Determinants of social desirability bias in sensitive surveys: A literature review. *Quality and Quantity, 47*(4), 2025–2047. https://doi.org/10.1007/s11135-011-9640-9

Kühn, S., Mascherek, A., Banaschewski, T., Bokde, A. L. W., Büchel, C., Quinlan, E. B., et al. (2020). Predicting change trajectories of neuroticism from baseline brain structure using whole brain analyses and latent growth curve models in adolescents. *Scientific Reports, 10*(1), 1207. https://doi.org/10.1038/s41598-020-58128-x

Kwon, J.-H., Chung, C.-S., & Lee, J. (2011). The effects of escape from self and interpersonal relationship on the pathological use of Internet games. *Community Mental Health Journal, 47*(1), 113–121. https://doi.org/10.1007/s10597-009-9236-1

Kwon, M., Lee, J.-Y., Won, W.-Y., Park, J.-W., Min, J.-A., Hahn, C., et al. (2013). Development and validation of a smartphone addiction scale (SAS). *PloS One, 8*(2), Article e56936. https://doi.org/10.1371/journal.pone.0056936

Kwon, M., Lee, J.-Y., Won, W.-Y., Park, J.-W., Min, J.-A., Hahn, C., et al. (2013a). Development and validation of a smartphone addiction scale (SAS). *PloS One, 8*(2), Article e56936. https://doi.org/10.1371/journal.pone.0056936

Laier, C., & Brand, M. (2017). Mood changes after watching pornography on the Internet are linked to tendencies towards Internet-pornography-viewing disorder. *Addictive Behaviors Reports, 5*, 9–13. https://doi.org/10.1016/j.abrep.2016.11.003

Laier, C., Wegmann, E., & Brand, M. (2018). Personality and cognition in gamers: Avoidance expectancies mediate the relationship between maladaptive personality traits and symptoms of internet-gaming disorder. *Frontiers in Psychiatry, 9*. https://doi.org/10.3389/fpsyt.2018.00304

Larsen, B., & Luna, B. (2018). Adolescence as a neurobiological critical period for the development of higher-order cognition. *Neuroscience & Biobehavioral Reviews, 94*, 179–195. https://doi.org/10.1016/j.neubiorev.2018.09.005

Lin, Y.-H., Chiang, C.-L., Lin, P.-H., Chang, L.-R., Ko, C.-H., Lee, Y.-H., et al. (2016). Proposed diagnostic criteria for smartphone addiction. *PloS One, 11*(11), Article e0163010. https://doi.org/10.1371/journal.pone.0163010

Lin, Y.-H., Lin, S.-H., Yang, C. C. H., & Kuo, T. B. J. (2017). *Psychopathology of everyday life in the 21st century: Smartphone addiction*. https://doi.org/10.1007/978-3-319-46276-9_20

Liu, D., & Campbell, W. K. (2017). The Big five personality traits, Big two metatraits and social media: A meta-analysis. *Journal of Research in Personality, 70*, 229–240. https://doi.org/10.1016/j.jrp.2017.08.004

Lo Coco, G., Salerno, L., Franchina, V., La Tona, A., Di Blasi, M., & Giordano, C. (2020). Examining bi-directionality between Fear of Missing Out and problematic smartphone use. A two-wave panel study among adolescents. *Addictive Behaviors, 106*, 106360. https://doi.org/10.1016/j.addbeh.2020.106360

Lüscher, C., Robbins, T. W., & Everitt, B. J. (2020). The transition to compulsion in addiction. *Nature Reviews Neuroscience, 21*(5), 247–263. https://doi.org/10.1038/s41583-020-0289-z

Marciano, L., & Camerini, A. L. (2020). Predicting problematic smartphone use from digital trace data and time distortion in adolescents. In *70th annual conference of the international communication association (ICA), 21st-25th may, converted from gold coast (Australia) to virtual due to COVID-19*.

Marciano, L., Camerini, A.-L., & Schulz, P. J. (2020). Neuroticism in the digital age: A meta-analysis. *Computers in Human Behavior Reports, 2*, 100026. https://doi.org/10.1016/j.chbr.2020.100026

Marriott, T. C., & Buchanan, T. (2014). The true self online: Personality correlates of preference for self-expression online, and observer ratings of personality online and offline. *Computers in Human Behavior, 32*, 171–177. https://doi.org/10.1016/j.chb.2013.11.014

Martini, M., Heinz, A., Hinterholzer, J., Martini, C., & Sachse, P. (2020). Effects of wakeful resting versus social media usage after learning on the retention of new memories. *Applied Cognitive Psychology, 34*(2), 551–558. https://doi.org/10.1002/acp.3641

Masson, M. E. J. (2011). A tutorial on a practical Bayesian alternative to null-hypothesis significance testing. *Behavior Research Methods, 43*(3), 679–690. https://doi.org/10.3758/s13428-010-0049-5

McCain, J. L., & Campbell, W. K. (2018). Narcissism and social media use: A meta-analytic review. *Psychology of Popular Media Culture, 7*(3), 308–327. https://doi.org/10.1037/ppm0000137

McElhaney, K. B., Antonishak, J., & Allen, J. P. (2008). "They like me, they like me not": Popularity and adolescents' perceptions of acceptance predicting social functioning over time. *Child Development, 79*(3), 720–731. https://doi.org/10.1111/j.1467-8624.2008.01153.x

Mihordin, R. (2012). Behavioral addition—quo vadis? *The Journal of Nervous and Mental Disease, 200*(6), 489–491. https://doi.org/10.1097/NMD.0b013e318257c503

Moilanen, K. L., Shaw, D. S., & Maxwell, K. L. (2010). Developmental cascades: Externalizing, internalizing, and academic competence from middle childhood to early adolescence. *Development and Psychopathology, 22*(3), 635–653. https://doi.org/10.1017/S0954579410000337

Mund, M., & Nestler, S. (2019). Beyond the Cross-Lagged Panel Model: Next-generation statistical tools for analyzing interdependencies across the life course. *Advances in Life Course Research, 41*, 100249. https://doi.org/10.1016/j.alcr.2018.10.002

Murray, A. L., Caye, A., McKenzie, K., Auyeung, B., Murray, G., Ribeaud, D., et al. (2020). Reciprocal developmental relations between ADHD and anxiety in adolescence: A within-person longitudinal analysis of commonly Co-occurring symptoms. *Journal of Attention Disorders*. https://doi.org/10.1177/1087054720908333, 1087054720908333.

Murray, A. L., Eisner, M., & Ribeaud, D. (2020). Within-person analysis of developmental cascades between externalising and internalising problems. *Journal of Child Psychology and Psychiatry, 61*(6), 681–688. https://doi.org/10.1111/jcpp.13150

Murray, A. L., Zych, I., Ribeaud, D., & Eisner, M. (2021). Developmental relations between ADHD symptoms and bullying perpetration and victimization in adolescence. *Aggressive Behavior, 47*(1), 58–68. https://doi.org/10.1002/ab.21930

Nickerson, A. B., & Nagle, R. J. (2005). Parent and peer attachment in late childhood and early adolescence. *The Journal of Early Adolescence, 25*(2), 223–249. https://doi.org/10.1177/0272431604274174

Noe, B., Turner, L. D., Linden, D. E. J., Allen, S. M., Winkens, B., & Whitaker, R. M. (2019). Identifying indicators of smartphone addiction through user-app interaction. *Computers in Human Behavior, 99*, 56–65. https://doi.org/10.1016/j.chb.2019.04.023

Odgers, C. (2018). Smartphones are bad for some teens, not all. *Nature, 554*(7693), 432–434. https://doi.org/10.1038/d41586-018-02109-8

Olsen, C. M. (2011). Natural rewards, neuroplasticity, and non-drug addictions. *Neuropharmacology, 61*(7), 1109–1122. https://doi.org/10.1016/j.neuropharm.2011.03.010

Oulasvirta, A., Rattenbury, T., Ma, L., & Raita, E. (2012). Habits make smartphone use more pervasive. *Personal and Ubiquitous Computing, 16*(1), 105–114. https://doi.org/10.1007/s00779-011-0412-2

Palfrey, J. G., & Gasser, U. (2011). *Born digital: Understanding the first generation of digital natives*. ReadHowYouWant.com.

Panova, T., & Carbonell, X. (2018). Is smartphone addiction really an addiction? *Journal of Behavioral Addictions, 7*(2), 252–259. https://doi.org/10.1556/2006.7.2018.49

Pereira, F. S., Bevilacqua, G. G., Coimbra, D. R., & Andrade, A. (2020). *Impact of problematic smartphone use on mental health of adolescent students: Association with mood, symptoms of depression, and physical activity*. Cyberpsychology, Behavior, and Social Networking. https://doi.org/10.1089/cyber.2019.0257

Perugini, M. L. L., & Solano, A. C. (2020). Normal and maladaptive personality traits as predictors of motives for social media use and its effects on well-being. *Psychological Reports*. https://doi.org/10.1177/0033294120922495, 0033294120922495.

Przybylski, A. K., Murayama, K., DeHaan, C. R., & Gladwell, V. (2013). Motivational, emotional, and behavioral correlates of fear of missing out. *Computers in Human Behavior, 29*(4), 1841–1848. https://doi.org/10.1016/j.chb.2013.02.014

R Core Team. (2013). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. http://www.R-project.org/.

Raj, K., & Verdejo-Garcia, A. (2020). Chapter 2—from impulses to compulsions. In A. Verdejo-Garcia (Ed.), *Cognition and addiction* (pp. 9–15). Academic Press. https://doi.org/10.1016/B978-0-12-815298-0.00002-2.

de Reuver, M., & Bouwman, H. (2015). Dealing with self-report bias in mobile Internet acceptance and usage studies. *Information & Management, 52*(3), 287–294. https://doi.org/10.1016/j.im.2014.12.002

Rideout, V., & Robb, M. B. (2019). *The common sense census: Media use by tweens and teens*. Common Sense Media. https://www.prnewswire.com/news-releases/the-common-sense-census-media-use-by-tweens-and-teens-new-research-finds-youtube-videos-beat-out-tv-and-video-games-as-entertainment-of-choice-for-tweens-and-teens-300946772.html.

Romero, E., & Alonso, C. (2019). *Maladaptative personality traits in adolescence: Behavioural, emotional and motivational correlates of the pid-5-bf scales*. Psicothema (Oviedo).

Rosegrant, J. (2012). Technologically altered reality inside the therapist's office. *Psychoanalytic Psychology, 29*(2), 226–240. https://doi.org/10.1037/a0025329

Rosenberg, K. P. (2014). *Behavioral addictions: Criteria, evidence, and treatment*. Academic Press.

Rosseel, Y. (2012). lavaan: An R package for structural equation modeling. *Journal of Statistical Software, 48*(1), 1–36. https://doi.org/10.18637/jss.v048.i02

Rozgonjuk, D., & Elhai, J. D. (2019). Emotion regulation in relation to smartphone use: Process smartphone use mediates the association between expressive suppression and problematic smartphone use. *Current Psychology, 1–10*. https://doi.org/10.1007/s12144-019-00271-4

Rozgonjuk, D., Kattago, M., & Täht, K. (2018). Social media use in lectures mediates the relationship between procrastination and problematic smartphone use. *Computers in Human Behavior, 89*, 191–198. https://doi.org/10.1016/j.chb.2018.08.003

Rozgonjuk, D., Levine, J. C., Hall, B. J., & Elhai, J. D. (2018). The association between problematic smartphone use, depression and anxiety symptom severity, and objectively measured smartphone use over one week. *Computers in Human Behavior, 87*, 10–17. https://doi.org/10.1016/j.chb.2018.05.019

Rozgonjuk, D., Pruunsild, P., Jürimäe, K., Schwarz, R.-J., & Aru, J. (2020). Instagram use frequency is associated with problematic smartphone use, but not with depression and anxiety symptom severity. *Mobile Media & Communication, 8*(3), 400–418. https://doi.org/10.1177/2050157920910190

RSPH. (2017). *#StatusofMind*. https://www.rsph.org.uk/our-work/campaigns/status-of-mind.html.

Ryding, F. C., & Kuss, D. J. (2020). Passive objective measures in the assessment of problematic smartphone use: A systematic review. *Addictive Behaviors Reports, 11*, 100257. https://doi.org/10.1016/j.abrep.2020.100257

Schimmenti, A., Musetti, A., Costanzo, A., Terrone, G., Maganuco, N. R., Aglieri Rinella, C., et al. (2019). The unfabulous four: Maladaptive personality functioning, insecure attachment, dissociative experiences, and problematic internet use among young adults. *International Journal of Mental Health and Addiction*. https://doi.org/10.1007/s11469-019-00079-0

Schultze-Lutter, F., Michel, C., Ruhrmann, S., & Schimmelmann, B. G. (2014). Prevalence and clinical significance of DSM-5–attenuated psychosis syndrome in adolescents and young adults in the general population: The bern epidemiological at-risk (BEAR) study. *Schizophrenia Bulletin, 40*(6), 1499–1508. https://doi.org/10.1093/schbul/sbt171

Shaw, M., & Black, D. W. (2008). Internet addiction. *CNS Drugs, 22*(5), 353–365. https://doi.org/10.2165/00023210-200822050-00001

Škařupová, K., Ólafsson, K., & Blinka, L. (2016). The effect of smartphone use on trends in European adolescents' excessive Internet use. *Behaviour & Information Technology, 35*(1), 68–74. https://doi.org/10.1080/0144929X.2015.1114144

Sohn, S., Rees, P., Wildridge, B., Kalk, N. J., & Carter, B. (2019). Prevalence of problematic smartphone usage and associated mental health outcomes amongst children and young people: A systematic review, meta-analysis and grade of the evidence. *BMC Psychiatry, 19*(1), 356. https://doi.org/10.1186/s12888-019-2350-x

Somerville, L. H. (2013). The teenage brain: Sensitivity to social evaluation. *Current Directions in Psychological Science, 22*(2), 121–127. https://doi.org/10.1177/0963721413476512

Squires, L. R., Hollett, K. B., Hesson, J. B., & Harris, N. (2020). Psychological distress, emotion dysregulation, and coping behaviour: A theoretical perspective of problematic smartphone use. *International Journal of Mental Health and Addiction*. https://doi.org/10.1007/s11469-020-00224-0

Steinberg, L. (2010). A dual systems model of adolescent risk-taking. *Developmental PsychobiologyThe Journal of the International Society for Developmental Psychobiology, 52*(3), 216–224. https://doi.org/10.1002/dev.20445, 52(3), 216–224.

Steinberg, L. (2016). *Adolescence* (11th ed.). McGraw-Hill Education.

Stein, D. J., Hollander, E., Simeon, D., & Cohen, L. (1994). Impulsivity scores in patients with obsessive-compulsive disorder. *The Journal of Nervous and Mental Disease, 182*(4), 240–241. https://doi.org/10.1097/00005053-199404000-00009

Stier, S., Breuer, J., Siegers, P., & Thorson, K. (2019). Integrating survey data and digital trace data: Key issues in developing an emerging field. *Social Science Computer Review*. https://doi.org/10.1177/0894439319843669, 089443931984366.

Suls, J., & Martin, R. (2005). The daily life of the garden-variety neurotic: Reactivity, stressor exposure, mood spillover, and maladaptive coping. *Journal of Personality, 73*(6), 1485–1509. https://doi.org/10.1111/j.1467-6494.2005.00356.x

Süss, D. D., Waller, G., Jael, B., Lilian, S., Gregor, W., Céline, K., et al. (2020). *Rapporto sui risultati dello studio JAMES 2020*.

Süss, D. D., Waller, G., Lilian, S., Gregor, W., Jael, B., Céline, K., et al. (2018). *James – youth, activities, media—survey Switzerland*. Zürcher Hochschule für Angewandte Wissenschaften. https://www.zhaw.ch/storage/psychologie/upload/forschung/medienpsychologie/james/2018/Report_JAMES_2018.pdf.

Thomas, M. (2011). *Deconstructing digital natives: Young people, technology, and the new literacies*. Taylor & Francis.

Throuvala, M. A., Griffiths, M. D., Rennoldson, M., & Kuss, D. J. (2019). Motivational processes and dysfunctional mechanisms of social media use among adolescents: A qualitative focus group study. *Computers in Human Behavior, 93*, 164–175. https://doi.org/10.1016/j.chb.2018.12.012

Twenge, J. M., Martin, G. N., & Campbell, W. K. (2018). Decreases in psychological well-being among American adolescents after 2012 and links to screen time during the rise of smartphone technology. *Emotion, 18*(6), 765–780. https://doi.org/10.1037/emo0000403

Twomey, C., & O'Reilly, G. (2017). Associations of self-presentation on Facebook with mental health and personality variables: A systematic review. *Cyberpsychology, Behavior, and Social Networking, 20*(10), 587–595. https://doi.org/10.1089/cyber.2017.0247

Vahedi, Z., & Saiphoo, A. (2018). The association between smartphone use, stress, and anxiety: A meta-analytic review. *Stress and Health: Journal of the International Society for the Investigation of Stress, 34*(3), 347–358. https://doi.org/10.1002/smi.2805

Valkenburg, P. M., & Peter, J. (2007). Preadolescents' and adolescents' online communication and their closeness to friends. *Developmental Psychology, 43*(2), 267–277. https://doi.org/10.1037/0012-1649.43.2.267

Valkenburg, P. M., & Piotrowski, J. T. (2017). *Plugged in: How media attract and affect youth*. New HavenYale University Press. https://doi.org/10.12987/yale/9780300218879.001.0001

van Velthoven, M. H., Powell, J., & Powell, G. (2018). Problematic smartphone use: Digital approaches to an emerging public health problem. *DIGITAL HEALTH, 4*. https://doi.org/10.1177/2055207618759167, 2055207618759167.

Wagenmakers, E.-J. (2007). A practical solution to the pervasive problems ofp values. *Psychonomic Bulletin & Review, 14*(5), 779–804. https://doi.org/10.3758/BF03194105

Waller, G., Willemse, I., Genner, S., Suter, L., & Süss, D. (2016). *James - jugend, aktivitäten, medien—erhebung schweiz*. https://www.zhaw.ch/storage/psychologie/upload/forschung/medienpsychologie/james/2016/Ergebnisbericht_JAMES_2016.pdf.

Wang, J., Wang, P., Yang, X., Zhang, G., Wang, X., Zhao, F., et al. (2019). Fear of missing out and procrastination as mediators between sensation seeking and adolescent smartphone addiction. *International Journal of Mental Health and Addiction, 17*(4), 1049–1062. https://doi.org/10.1007/s11469-019-00106-0

Ward, A. F., Duke, K., Gneezy, A., & Bos, M. W. (2017). Brain drain: The mere presence of one's own smartphone reduces available cognitive capacity. *Journal of the Association for Consumer Research, 2*(2), 140–154.

Watson, D., & Clark, L. A. (2020). Personality traits as an organizing framework for personality pathology. *Personality and Mental Health, 14*(1), 51–75. https://doi.org/10.1002/pmh.1458

Weiss, B., Campbell, W. K., Lynam, D. R., & Miller, J. D. (2019). A Trifurcated Model of Narcissism: On the pivotal role of trait antagonism. In *The handbook of antagonism: Conceptualizations, assessment, consequences, and treatment of the low end of agreeableness* (pp. 221–235). Elsevier Academic Press. https://doi.org/10.1016/B978-0-12-814627-9.00015-3.

Weller, E. B., Kloos, A., Kang, J., & Weller, R. A. (2006). Depression in children and adolescents: Does gender make a difference? *Current Psychiatry Reports, 8*(2), 108–114. https://doi.org/10.1007/s11920-006-0007-1

Wilmer, H. H., Sherman, L. E., & Chein, J. M. (2017). Smartphones and cognition: A review of research exploring the links between mobile technology habits and cognitive functioning. *Frontiers in Psychology, 8*. https://doi.org/10.3389/fpsyg.2017.00605

Wolke, D., Waylen, A., Samara, M., Steer, C., Goodman, R., Ford, T., et al. (2009). Selective drop-out in longitudinal studies and non-biased prediction of behaviour disorders. *The British Journal of Psychiatry, 195*(3), 249–256. https://doi.org/10.1192/bjp.bp.108.053751

World Health Organization. (2018). *International classification of diseases for mortality and morbidity statistics (11th Revision)*. https://icd.who.int/browse11/l-m/en.

Wright, A. G. C., Pincus, A. L., Thomas, K. M., Hopwood, C. J., Markon, K. E., & Krueger, R. F. (2013). Conceptions of narcissism and the DSM-5 pathological personality traits. *Assessment, 20*(3), 339–352. https://doi.org/10.1177/1073191113486692

Zappulla, C., Pace, U., D'Urso, G., & Pace, U. (2019). Internalizing problems as a mediator in the relationship between low effortful control and internet abuse in adolescence: A three-wave longitudinal study. *Computers in Human Behavior, 92*, 47–54.

Zhitomirsky-Geffet, M., & Blau, M. (2016). Cross-generational analysis of predictive factors of addictive behavior in smartphone usage. *Computers in Human Behavior, 64*, 682–693. https://doi.org/10.1016/j.chb.2016.07.061