# #ConnectedTeens

## Social media use and adolescent wellbeing

Maartje Boer

# #ConnectedTeens:
Social media use and adolescent wellbeing

Maartje Boer

| | |
|---|---|
| ISBN: | 978-94-6458-108-9 |
| Cover design & Lay-out: | Publiss \| www.publiss.nl |
| Print: | Ridderprint \| www.ridderprint.nl |

# #ConnectedTeens: Social media use and adolescent wellbeing

## #VerbondenTieners: Gebruik van sociale media en welbevinden van adolescenten

(met een samenvatting in het Nederlands)

# Proefschrift

ter verkrijging van de graad van doctor aan de
Universiteit Utrecht
op gezag van de
rector magnificus, prof.dr. H.R.B.M. Kummeling,
ingevolge het besluit van het college voor promoties
in het openbaar te verdedigen op

vrijdag 22 april 2022 des middags te 12.15 uur

door

**Maartje Boer**

geboren op 26 maart 1990
te Wageningen

**Promotor:**

Prof. Dr. C. Finkenauer

**Copromotoren:**

Dr. G. W. J. M. Stevens
Dr. R. J. J. M. van den Eijnden

**Beoordelingscommissie:**

| | |
|---|---|
| Prof. Dr. P. M. Valkenburg | Universiteit van Amsterdam |
| Prof. Dr. L. Keijsers | Erasmus Universiteit Rotterdam |
| Prof. Dr. M. Kleinjan | Universiteit Utrecht |
| Prof. Dr. T. F. M. ter Bogt | Universiteit Utrecht |
| Dr. M. Peeters | Universiteit Utrecht |

# Table of Contents

# CHAPTER 1

## INTRODUCTION

# Introduction

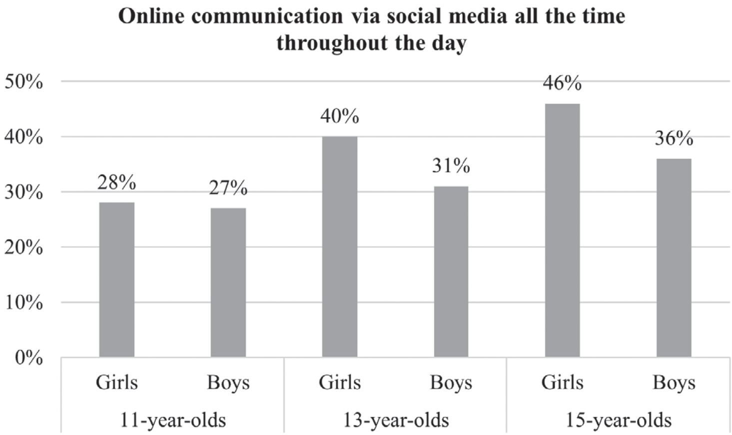
Social media have become increasingly popular in the past decades (Anderson & Smith, 2021), especially among early and middle adolescents (Anderson & Jiang, 2018; Lenhart et al., 2015). Social media are social network sites, such as Instagram and Facebook, and instant messengers, including SnapChat and Whatsapp. Social network sites allow users to create and maintain a personal profile with photos, videos, and texts to share with an online social network. Instant messengers facilitate sending personalized direct messages to others through private chat functions. Many adolescents use social media through internet applications on their smartphones (Eurostat, 2015), which allows them to access social media any time at any place.

Research among 13- to 17-year-olds U.S. adolescents showed that the percentage of adolescents reporting being almost online constantly has almost doubled within three years: from 24% in 2015, to 45% in 2018 (Anderson & Jiang, 2018; Lenhart et al., 2015). Findings from research among European and Canadian adolescents indicated that in 2017 and 2018, 41% of all 15-year-olds interacted with friends and others through social media almost all the time throughout the day (Inchley et al., 2020b). In other research among European adolescents collected between 2017 and 2019 it was found that 81% of the 15- and 16-year-olds reported using a smartphone to access internet several times or almost all the time throughout the day. Among this group, the average time spent online was almost four hours a day and 77% reported visiting social network sites at least once a day (Smahel et al., 2020). These studies illustrate that, nowadays, many adolescents have integrated social media use (SMU) into their daily lives. Furthermore, social media are popular across both genders and during both early and middle adolescence (Inchley et al., 2020b; Smahel et al., 2020), although research showed that girls use social media more frequently than boys and the popularity of social media increases with age (Figure 1.1; Inchley et al., 2020b).

From a developmental point of view, it is understandable why social media are so popular among young adolescents. During early adolescence, making close friends, belonging to peer groups, and being accepted by peers becomes increasingly important. More specifically, peers offer young adolescents opportunities to experiment with and discover new behaviors, morals, and beliefs and as such, to become more autonomous from parents

**Figure 1.1**

*Percentage of Adolescents Reporting Online Communication via Social Media Almost All the Time Throughout the Day*




*Note*. Data source: HBSC 2017/2018, *n* = 227,441 adolescents from 45 countries in Europe and Canada (Inchley et al., 2020b)

and to develop their individual self (Brechwald & Prinstein, 2011; Steinberg & Morris, 2001). Social media allow adolescents to fulfil these social needs (Granic et al., 2020; Valkenburg & Peter, 2011), for example by forming and maintaining friendships by befriending peers on social network sites, direct messaging with friends through instant messengers, and receiving approval from peers through *likes*. Furthermore, in early and middle adolescence, it becomes highly important for adolescents to document and share their personal narratives and to learn from their peers' personal life stories (Granic et al., 2020). The satisfaction of these needs is also facilitated by social media, because they allow adolescents to describe their lives through uploading photos or videos of themselves (and their friends) or activities on their social network site profile and to monitor their peers by browsing through photos, videos, and texts of others (Granic et al., 2020; Veissière & Stendel, 2018). In other words, social media can amplify processes that are relevant to young adolescents' individual development.

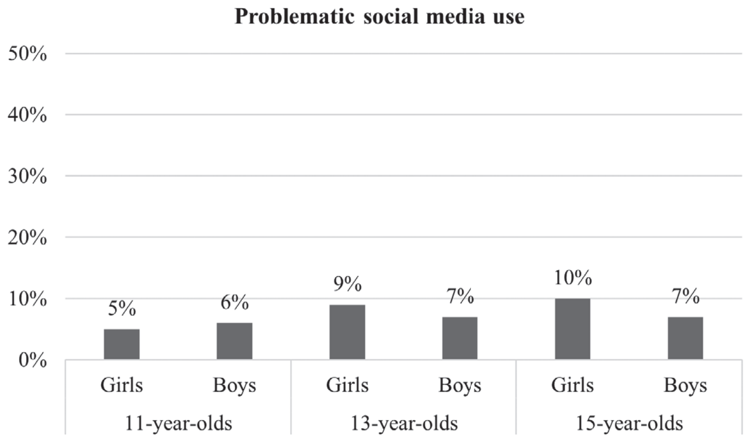
## Problematic SMU

Although SMU can be understood as a behavior that contributes to the development of young adolescents nowadays, concerns have been raised about *problematic SMU*, which also has been defined as social media addiction, social media disorder, or compulsive social media use (Lee et al., 2017). Problematic SMU is conceptually different from the *intensity* of SMU, because problematic SMU is characterized by symptoms of addiction to social media, whereas the intensity of SMU refers to nothing more than the time spent (e.g., hours per day) or frequency of SMU (e.g., number of times viewing per day). Although it is common that adolescents use social media intensively (Anderson & Jiang, 2018; Smahel et al., 2020), scholars consider problematic SMU as exceptional behavior (Griffiths, 2013; Kardefelt-Winther et al., 2017). In line with this suggestion, a meta-analysis using samples across 32 nations estimated the average prevalence rate of problematic SMU at 5% at the population level, although this rate varied by demographic variables, whereby samples with young respondents showed higher rates than samples with adult respondents (Cheng et al., 2021). Other international research among adolescents reports a prevalence rate of 7%, with (small) differences by gender and age (Figure 1.2; Inchley et al., 2020b).

In short, adolescents who display problematic SMU are incapable of regulating their use and/or have social media on top of their mind constantly (Griffiths et al., 2014). Problematic users may be 'addicted' to the social rewards of SMU, such as the involvement with peers and other people by monitoring them online, and the reassurance to be noticed by others by posting personal content on social media (Veissière & Stendel, 2018). Problematic SMU is often defined by six addiction criteria that parallel substance-related addiction criteria, including being *preoccupied* with social media by constantly thinking about it, using social media to *escape* from negative feelings, increasing *tolerance* levels by wanting to use social media more and more to achieve satisfaction, experiencing *withdrawal* symptoms when SMU is not possible, having *conflicts* with, for example, close relationships due to excessive SMU, and engaging in *persistent* SMU by being unable to control SMU (Andreassen et al., 2012; Bányai et al., 2017; Kuss et al., 2014). Yet, unlike other non-substance related addictions, including gambling and internet gaming addiction, neither the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) nor the International Classification of Disease (ICD-11) recognize a behavioral addiction related to SMU (American Psychiatric Association, 2013; World Health Organization, 2019). This is understandable, because social media became

**Figure 1.2**

*Percentage of Adolescents Reporting Problematic Social Media Use*




*Note*. Data source: HBSC 2017/2018, *n* = 227,441 adolescents from 45 countries in Europe and Canada (Inchley et al., 2020b)

particularly popular after the rise in smartphone adoption around 2012 (Twenge, Martin, et al., 2018), which implies that SMU is a relatively new phenomenon. It generally takes decades of research before a certain behavioral pattern is recognized as an addiction in a classification system. Therefore, in line with the commonly used definition among scholars, we define SMU that is characterized by addiction-like behaviors as *problematic SMU* (Lee et al., 2017).

In many studies, problematic SMU is defined by the presence of a number of addiction criteria, for example, when at least four out of six criteria are reported (Andreassen et al., 2012; Cheng et al., 2021). Such a definition is useful to identify and study the most extreme behaviors that are possibly the most clinically relevant. Some studies in this dissertation defined problematic SMU on a continuous scale, indicated by the number of present criteria, which in some chapters is referred to as the level of *SMU problems*. Throughout the dissertation, we use the terms problematic SMU and SMU problems interchangeably.

Review studies showed that problematic SMU is positively correlated with the intensity of SMU with a small to moderate effect size (Frost & Rickwood, 2017; Parry et al., 2020). This correlation and its magnitude seem plausible, because some problematic users may engage in high SMU intensity as a result of their inability to control their SMU and to fulfil their cravings towards SMU. Yet, the two SMU behaviors are also different, because some adolescents who use SMU intensively may be well able to regulate their SMU. Furthermore, some problematic users may not show extremely high levels of SMU intensity, for example when they have a small online social network to interact with, but are nonetheless preoccupied with social media by constantly thinking it. Overall, SMU problems and intensity are related, but different dimensions of SMU.

## SMU and Wellbeing

With the increasing popularity of social media among youth (Anderson & Jiang, 2018), both concerns and research on the potential impact of adolescents' SMU on their wellbeing increased considerably in the past decade. To illustrate, a basic search assignment in search engine Scopus on adolescents' SMU and wellbeing in the period between 2016 and 2020 returned 4,081 publications (e.g., articles, book chapters), whereas for the period between 2011 and 2015, the same search assignment yielded 755 publications[1]. There are concerns that SMU in general (often without making a distinction between SMU intensity or SMU problems) is detrimental to various domains of wellbeing (Underwood & Ehrenreich, 2017; Unicef, 2017). For example, it has been argued that SMU impairs mental health, such as increasing symptoms of Attention Deficit Hyperactivity Disorder (ADHD)-symptoms (Wiederhold, 2019), although studies testing this suggestion are scarce. The ongoing interruptions by social media notifications may reinforce intensive task-switching between online and offline activities. This may be detrimental to adolescents' capability of filtering relevant from irrelevant information, which may reinforce attention deficits (Baumgartner et al., 2017). Consistent with this suggestion, cross-sectional studies showed that the higher adolescents' *SMU intensity*, the higher their level of ADHD-symptoms (Barry et al., 2017; Levine et al., 2007). Also, research among Dutch adolescents showed that *problematic SMU* was associated with inattention and impulsivity (Van den Eijnden et al., 2016).

In addition, it has been put forward that SMU harms other aspects of mental health, for example that it induces depressive symptoms and impairs life satisfaction. One explanation for this suggestion is that social media

[1] Boolean search term = (( "social media us*" OR "social network site us*" OR "instagram us*" OR "facebook us*" ) AND ( wellbeing OR "well-being" ) AND adolescents ).

users typically present themselves in an overly flattering way (Fardouly & Vartanian, 2016). Intensive exposure to such idealized portrayals of others may elicit upward social comparisons, such as the perception that others are more popular, attractive, or successful in life (Pera, 2018; Verduyn et al., 2020). Alternatively, high SMU intensity may go at the expense of meaningful offline activities, such as face-to-face socializing with friends or homework (Underwood & Ehrenreich, 2017). In addition, adolescents who spend more time online may be at higher risk for cybervictimization (Sampasa-Kanyinga & Hamilton, 2015). In turn, these factors may harm adolescents' mental health. In line with these concerns, large-scale cross-sectional research among U.S. and U.K. adolescents showed that higher *intensity* of SMU is associated with less happiness and more depressive symptoms (Kelly et al., 2018; Twenge, Martin, et al., 2018). Also, longitudinal studies showed that higher levels of SMU intensity predicted subsequent depressive symptoms and overall internalizing problems (Frison & Eggermont, 2017; Riehm et al., 2019). Furthermore, meta-analytic findings suggest that a higher intensity of Facebook use is associated with more depression, anxiety, and other mental health problems (Frost & Rickwood, 2017). In addition, several cross-sectional studies on adolescents showed that *problematic* SMU was related to worse psychological health, including higher levels of depressive symptoms, anxiety, and stress (Bányai et al., 2017; Pontes, 2017). Moreover, meta-analytic findings using adolescent and young adult samples showed a positive relation between problematic Facebook use and psychological distress (Marino et al., 2018b).

Together, these studies indicate that both the intensity of SMU and problematic SMU are related to lower mental health. However, many questions about these associations remain unanswered, which we outline below and aim to answer in this dissertation.

## Are SMU Intensity and SMU Problems Independently Related to Poorer Wellbeing?

A major disadvantage of the studies discussed above, that is central to this dissertation, is that these either studied the intensity of SMU or problematic SMU in relation with wellbeing, instead of simultaneously. However, the two different SMU behaviors are correlated with each other and the abovementioned studies suggest that both the intensity of SMU and problematic SMU are negatively related to wellbeing. As a result, it is unknown which SMU behavior induces negative associations with wellbeing. More specifically, it is unclear whether engaging in high SMU intensity is detrimental to wellbeing, as some studies have suggested (e.g., Kelly et al., 2018; Twenge et al., 2018), or whether these associations were spurious because they could be explained by problematic SMU. Given that nowadays many adolescents use social media intensively (Anderson & Jiang, 2018; Smahel et al., 2020), and the widespread concerns about the overuse of social media to adolescents' health (Orben, 2020b; Unicef, 2017), it is crucial to identify which type of SMU behavior induces potential harmful effects.

Possibly, adolescents engaging in high SMU intensity may be well able to combine their SMU with a healthy lifestyle, because high SMU intensity does not necessarily indicate any loss of control over SMU or interference with activities that are relevant to adolescent wellbeing, such as face-to-face contact with peers. Instead, high SMU intensity may be understood as a common adolescent behavior that is relevant to their individual development during adolescence. Detrimental consequences may rather emerge when adolescents' SMU is problematic, because in that case, adolescents have lost control over their SMU behavior. Put differently, adolescents who are using social media problematically have a decreased ability to regulate SMU impulses and constantly think about SMU (Griffiths, 2013; Griffiths et al., 2014). Such loss of agency over thoughts, emotions, and behaviors, may interfere with adolescents' daily lives and as such, be a source of decreased wellbeing. Thereby, problematic SMU may be more harmful to wellbeing than high levels of SMU intensity.

To our knowledge, only two prior studies have disentangled the effects of adolescents' intensity of SMU and problematic SMU. Based on longitudinal data that were also used in chapters included in this dissertation, Van den Eijnden and colleagues (2018) showed that SMU problems, but not SMU intensity, predicted lower levels of life satisfaction over time. In line with these findings, a cross-sectional study among U.S. young adults (aged 19 to 32) revealed that problematic SMU, but not the intensity if SMU, was associated with more depressive symptoms (Shensa et al., 2017). These studies provide important first insights into the differences between the intensity of SMU and problematic SMU, in particular in their differential associations with wellbeing. However, additional knowledge gaps related to SMU intensity, SMU problems, and wellbeing remain, which we discuss below and aim to answer in this dissertation.

## How Should We Measure Problematic SMU?

Although research on problematic SMU has grown in the past decade, validation research on instruments measuring problematic SMU lags behind. Several instruments have been developed, yet most of them have not been subjected to validation (Andreassen, 2015). Currently, only one instrument has been validated in nationally representative adolescent samples (Andreassen et al., 2016; Bányai et al., 2017; Lin et al., 2017). This instrument measures problematic SMU based on six criteria of addiction mentioned above, including preoccupation (i.e., salience), escape (i.e., mood modification), tolerance, withdrawal, relapse (i.e., persistence), and conflict (Andreassen et al., 2016; Griffiths, 2005). However, extending the measurement with additional items that measure negative consequences due to SMU possibly advances the measurement of problematic SMU, as problematic SMU refers to addiction-like SMU, and one of the core aspects of behavioral addiction is that the behavior in question impairs daily life (Kardefelt-Winther et al., 2017; Van Rooij et al., 2018). To facilitate future research on problematic SMU, it is essential that it is measured with a scale that encompasses all theoretical criteria of problematic SMU and furthermore, that this scale is found to be reliable and valid within a nationally representative sample. Future research on problematic SMU is considered important, given the growing evidence that problematic SMU is negatively associated with adolescent wellbeing (Marino et al., 2018b). Furthermore, a scale with good psychometric properties may provide health professionals with a psychometrically sound instrument to screen adolescents for problematic SMU.

In addition, there is no scale that measures problematic SMU for which the reliability and validity has been assessed and compared across different countries. Furthermore, it has not been investigated whether adolescents from different countries interpret the questions from a problematic SMU-scale in the same way, and thus whether the scale measures the same underlying construct cross-nationally. A valid and reliable instrument with equivalent interpretations across various national settings provides researchers worldwide with an instrument to accurately measure problematic SMU and furthermore, to compare their country-specific findings with research on problematic SMU in other national contexts. Additionally, validating a problematic SMU-scale cross-nationally provides global knowledge about the phenomenon, namely about the prevalence as well as the extent to which it is indicative of adolescent health risks worldwide.

### Are There Cross-National Differences in the Extent to Which SMU Intensity and SMU Problems Are Related to Wellbeing?

Up till now, studies on the association between SMU and wellbeing typically have used single-country data. As a consequence, we do not know whether the earlier found associations are country-specific or emerge across countries. That is, it remains unclear whether the association depends upon the national context in which adolescents grow up in. Research suggests that once risk behaviors, such as substance use, become accepted within a society, these behaviors become normalized (Haskuka et al., 2018; Sznitman et al., 2015). As a result, these risk behaviors are not indicative (anymore) for adolescents with problematic profiles, but instead, may represent well-adjusted adolescents (Sznitman et al., 2015). In a similar vein, when many adolescents show high levels of SMU intensity and/or SMU problems within a society, these behaviors may not or to a lesser extent be indicative of lower wellbeing within that society.

Theories on the effects of (social) media use often explain the effect while disregarding the wider contexts adolescents are in. Therefore, identifying in which national contexts particular SMU behaviors increase the risk of lower wellbeing advances current theory on social media effects. In doing so, to improve our understanding of SMU effects, it is important to highlight the differences between SMU intensity and SMU problems in how they relate to wellbeing. Furthermore, wellbeing is a broad concept that encompasses many facets. Given that SMU behaviors may be more strongly associated with some domains of wellbeing than others (Richards et al., 2015), it is essential to distinguish between multiple domains of wellbeing, such as adolescents' mental health, social wellbeing, and school wellbeing. Establishing in which national contexts high SMU intensity and SMU problems increase the risk of poorer wellbeing identifies in which national settings the implementation of intervention programs aimed at supporting adolescents with particular SMU behaviors could be most valuable.

## In Which Direction Are SMU Intensity and SMU Problems Related to Lower Wellbeing?

Another shortcoming of previous research is that they do not show whether lower wellbeing precedes from or follows after higher levels of SMU intensity or SMU problems, either because they largely used cross-sectional data, or longitudinal analysis that did not explore directionality (Bányai et al., 2017; Kelly et al., 2018; Shensa et al., 2017; Van den Eijnden et al., 2018). Theoretically, SMU intensity and SMU problems could both be causes as well as consequences of lower wellbeing. For example, as highlighted above, SMU may increase adolescents' ADHD-symptoms. Or, it may increase depressive symptoms, whereby upward social comparisons, displacement of schoolwork activities or face-to-face contacts, or cybervictimization possibly play a mediating role (Pera, 2018; Underwood & Ehrenreich, 2017; Verduyn et al., 2020). However, as mentioned earlier, such effects on wellbeing may rather be driven by adolescents' SMU problems than by their SMU intensity (Shensa et al., 2017; Van den Eijnden et al., 2018).

A reverse order, whereby lower wellbeing causes higher levels of SMU intensity or SMU problems, also seems plausible. For example, given that adolescents with ADHD-symptoms are typically sensitive to external distractors (American Psychiatric Association, 2013), they may have a limited ability to forego incoming notifications and messages through social media smartphone applications, and consequently they may often not be able to resist temptations to use social media. Or, adolescents with depressive symptoms may use social media intensively or become dependent on it to cope with or escape from their negative feelings, or to feel more positive about themselves (Caplan, 2003; Griffiths, 2013). It is unclear whether these aspects of lower wellbeing could reinforce high SMU intensity, SMU problems, or both.

Establishing the potential causal order of the relation between adolescents' SMU behaviors and specific aspects of their wellbeing enhances current theoretical knowledge on the emergence as well as potential impact of high SMU intensity and SMU problems. In doing so, disentangling SMU intensity and SMU problems in their association with wellbeing is considered important, because this identifies which particular SMU behavior precedes or follows from poorer wellbeing. Furthermore, distinguishing between different indicators of wellbeing, in particular mental health (i.e., ADHD-symptoms, depression symptoms, life satisfaction), when studying associations with SMU behaviors, further advances current knowledge. This namely reveals which aspect of wellbeing is (most) vulnerable to high SMU intensity and/or SMU problems and, reversely, which aspect of wellbeing (mostly) explains high SMU intensity and/or SMU problems.

## How Do SMU Problems Develop Over Time?

Problematic behaviors are typically not static, but, instead, show developmental trajectories depending on age or other biological, social, and cognitive developments. So far, it is unknown how SMU problems develop over time throughout adolescence. Research on deviant behaviors and mental health problems, such as aggression, delinquency, binge drinking, and depression, show that these behaviors typically develop through multiple trajectories throughout adolescence, including a persistently low, persistently high, and one or more variable trajectories (Bongers et al., 2004; Chassin et al., 2002; Dekker et al., 2007; Reinecke, 2006b). Considering SMU problems as deviant behaviors that are related to mental health problems, SMU problems may develop through comparable trajectories. So far, this has been unexplored. In addition, it has been put forward that adolescents with low mental health and poor social competencies are more likely to report SMU problems, because of their limited ability to regulate their SMU or because they prefer online interaction over face-to-face encounters due to their psychosocial vulnerabilities (Caplan, 2003; Davis, 2001; Mérelle et al., 2017; Wu et al., 2013). However, it is unclear whether these vulnerabilities increase the risk of, for example, temporarily or persistently high levels of SMU problems.

Given the increasing evidence that SMU problems threaten adolescents' wellbeing (Marino et al., 2018b; Van den Eijnden et al., 2018), it is important to identify whether, when, and for whom SMU problems increase, decrease, or persist over time. Not only does this information advance current theory on SMU problems by identifying the course of the behavior; it also allows researchers to identify in which period of adolescence and to whom prevention and intervention programs on problematic SMU may be most valuable. Furthermore, to enhance our understanding on (the development) of SMU problems even more, trajectories of adolescents' SMU problems should be studied in parallel with their SMU intensity, because this reveals the similarities or differences between the two SMU behaviors.

## Which Factors Influence the Association Between SMU Intensity and Wellbeing?

Although distinguishing SMU intensity and SMU problems is an important step towards improving our understanding in the association between SMU and wellbeing, there are other factors that may affect the association that have received little empirical attention thus far. More specifically, it has been postulated that the effect of SMU intensity on wellbeing depends on the activity the adolescent engages in (Verduyn et al., 2017). According to this view, *active* SMU activities, such as posting messages, photos, or videos and chatting with or responding to others on social media, are beneficial to wellbeing, because it enhances adolescents' social capital and sense of belonging. In contrast, *passive* SMU activities, such as scrolling through peers' messages, photos, and videos on social media, may be detrimental to wellbeing, because these activities expose adolescents to idealized unrealistic self-presentations of others, which induce envy and upward social comparison (Verduyn et al., 2017). In addition, according to the *Goldilocks hypothesis*, the relation between adolescents' SMU intensity and wellbeing follows an inverted u-shape, whereby moderate use could be advantageous to adolescents' wellbeing (Przybylski & Weinstein, 2017). Also, according to the *differential susceptibility to media effects model*, media effects differ across individuals, because they are contingent on, for example, dispositional characteristics (Valkenburg & Peter, 2013). Furthermore, the link between adolescents' SMU intensity and wellbeing may depend on methodological considerations, namely whether *within-* or *between-person* associations are studied. While the former indicate whether changes in two behaviors within a person are associated, the latter denote whether differences in two behaviors between persons are associated. It is not uncommon that within- and between-person associations differ in effect size or even direction (Hamaker, 2012).

Thus, not only does the association between adolescents' SMU intensity and wellbeing may depend on whether SMU problems are taken into account, it may also depend on the conceptualization of SMU intensity (i.e., active vs. passive), the (non)linearity of the association, individual differences, and the methodological approach (i.e., level of analysis). As such, more in-depth research, that systematically takes all these factors into account, is crucial to understand the relation between adolescents' SMU intensity and wellbeing, which is typically lacking in the aforementioned studies on SMU effects. Insights from a detailed analysis provide researchers with specific directions for future research on SMU effects. Furthermore, it informs parents and health professionals who are concerned with the wellbeing of adolescents about the extent to which SMU could be beneficial or harmful to wellbeing.

## Aims of the Dissertation

The overall aim of this dissertation is to improve our understanding of the association between SMU and wellbeing, with particular attention to the differences between SMU intensity and SMU problems in how they relate to specific domains of adolescent wellbeing. In all chapters of this dissertation, we focused on adolescents in high school (i.e., aged 11 to 16). Studying associations between adolescents' SMU and wellbeing during this period of adolescence considered important, because in this period, social media are omnipresent and play an important role in their individual development (Granic et al., 2020). Given the prominent role of social media in adolescents' daily lives and the possible effects on different aspects of their wellbeing, it is essential to study the relation between adolescents' SMU and wellbeing both for science and possibly for the development of public health policies.

In this dissertation, wellbeing often refers to mental health, indicated by positive mental health (e.g., life satisfaction) as well as mental health problems (e.g., ADHD-symptoms, depressive symptoms). In some chapters, wellbeing is also indicated by social wellbeing (e.g., friends support), school wellbeing (e.g., school satisfaction), and/or sleep (e.g., sleep duration). To study SMU behaviors and their relation with adolescent wellbeing, the chapters in this dissertation aim to answer the research questions highlighted above. More specifically, in response to the limited validation work on scales that measure problematic SMU, in **Chapter 2**, we validated the Social Media Disorder (SMD)-scale (Van den Eijnden et al., 2016) among a cross-sectional representative sample of Dutch adolescents. Here, we investigated the structural validity, reliability, measurement invariance, item score patterns, and criterion validity of the scale using (multigroup) Confirmatory Factor Analysis, Exploratory Factor analysis, Item Response Theory, Latent Class Analysis, and multivariate regression analysis. To test whether the scale has good psychometric properties across multiple national settings, in **Chapter 3**, we compared the psychometric properties of the SMD-scale across 44 countries within the European region and Canada. In particular, we compared the structural validity, reliability, and criterion validity of the scale across countries. In addition, we examined whether the factor structure of the scale was measurement invariant across countries, gender, and age.

In light of the abundance of single-country studies on the association between SMU behaviors and wellbeing, in **Chapter 4**, we conducted multilevel models on cross-national data to investigate whether intense and problematic SMU and their associations with wellbeing varied by the way in which social media were adopted within the countries' adolescent population, indicated by the country-level prevalence of intensive and problematic SMU. Here, wellbeing was indicated by mental health[2] (i.e., life satisfaction, psychological complaints), social wellbeing (i.e., family support, friends support), and school wellbeing (i.e., school satisfaction, schoolwork pressure).

The remaining chapters zoom in on the association between SMU behaviors and wellbeing by studying adolescents' SMU intensity, SMU problems, and wellbeing over time within adolescents. More specifically, in the next two chapters, we aimed to address the question whether lower wellbeing, in particular mental health, precedes or follows from SMU intensity and SMU problems, using longitudinal data and Random Intercept Cross-Lagged Panel Modelling. In **Chapter 5**, we studied the direction of the association between SMU intensity, SMU problems, and ADHD-symptoms. Extending the work in Chapter 5, in **Chapter 6**, we investigated the direction of the association between SMU intensity, SMU problems, and life satisfaction as well as depressive symptoms. In addition, we examined whether these associations were mediated by different mechanisms, including upward social comparisons, cybervictimization, decreased face-to-face contacts, and worsened subjective school achievements.

In addition, considering the lack of studies investigating problematic SMU from a developmental perspective, to gain knowledge on how SMU problems develop throughout adolescence, in **Chapter 7**, we explored trajectories of SMU problems over time using Latent Class Growth Analysis.

[2] In Chapter 4, we refer to mental wellbeing instead of mental health.

To further improve our understanding of the development of SMU problems, we studied adolescents' trajectories of SMU problems in parallel with their trajectories of SMU intensity[3]. Furthermore, based on multinomial regression, we examined which wellbeing indicators predicted these co-trajectories. Here, wellbeing referred to mental health[4] (i.e., life satisfaction, self-esteem, ADHD-symptoms) and social wellbeing[5] (i.e., friendship competencies).

Finally, to further extend current knowledge on the association between SMU behaviors and wellbeing, in **Chapter 8**, we used multilevel modelling on longitudinal data to study the association between SMU intensity and wellbeing in more detail. More specifically, we examined five theoretical and methodological factors that possibly affect the association between adolescents' SMU intensity and life satisfaction, namely how SMU is conceptualized (i.e., active or passive SMU), whether it is studied (non)linear, whether individual differences are considered, whether problematic SMU is taken into account, and the level of analyses (i.e., within- or between-person level).

## Data

The chapters in this dissertation used large-scale nationally and internationally representative cross-sectional data as well as longitudinal data of adolescents aged 11 to 16 from the Health Behaviour in School-aged Children (HBSC) study (Inchley et al., 2020b; Stevens et al., 2018) and the Digital Youth (DiYo) project (Van den Eijnden et al., 2018). The HBSC-study is a cross-national study carried out every four years since 1983 in collaboration with the World Health Organization (WHO) Regional Office for Europe. It monitors adolescents' health behaviors, wellbeing, and social context using self-report surveys administered in large-scale nationally representative samples. The HBSC-data were used in Chapters 2, 3, and 4. Table 1.1 provides an overview of the sample size and characteristics of these studies.

The DiYo-project is a longitudinal study on self-report online behaviors and wellbeing among Dutch high school adolescents. Data were collected in February-April of 2015 until 2019 with yearly time intervals. Chapters 5 until 8 were based on samples from the DiYo project, although they used different

[3] In Chapter 7, we refer to SMU frequency instead of SMU intensity.

[4] In Chapter 7, we refer to subjective wellbeing (life satisfaction, self-esteem) and self-control (attention deficits, impulsivity).

[5] In Chapter 7, we refer to social competencies instead of social wellbeing.

**Table 1.1**

*Chapter Overview With Sample Information*

| Chapter | Title | Sample | Sample characteristics | Sample size |
|---|---|---|---|---|
| 2 | Validation of the Social Media Disorder-Scale in adolescents: Findings from a large-scale nationally representative sample | HBSC Netherlands, cross-sectional, 2017 | Age = 12-16 M = 13.9 SD = 1.4 | 6,626 |
| 3 | Cross-national validation of the Social Media Disorder-scale: Findings from adolescents from 44 countries | HBSC international, cross-sectional, 2017/2018 | Age = 11, 13, and 15 M = 13.5 SD = 1.6 | 222,532 adolescents from 44 countries |
| 4 | Adolescents' intense and problematic social media use and their wellbeing in 29 countries | HBSC international, cross-sectional, 2017/2018 | Age = 11, 13, and 15 M = 13.5 SD = 1.6 | 154,981 adolescents from 29 countries |
| 5 | Attention deficit hyperactivity disorder-symptoms, social media use intensity, and social media use problems in adolescents: Investigating directionality | DiYo, longitudinal, 3 waves, 2015-2017 | Age (T1) = 11-15 M = 12.9 SD = 0.7 | 543 |
| 6 | Social media use intensity, social media use problems, and mental health among adolescents: Investigating directionality and mediating processes | DiYo, longitudinal, 3 waves, 2016-2018 | Age (T1) = 10-16 M = 13.1 SD = 0.8 | 2,109 |
| 7 | The course of problematic social media use in young adolescents: A latent class growth analysis | DiYo, longitudinal, 4 waves, 2015-2019 | Age (T1) = 11-15 M = 12.5 SD = 0.6 | 1,419 |
| 8 | The complex association between social media use intensity and adolescent wellbeing: A longitudinal investigation of five factors that may affect the association | DiYo, longitudinal, 4 waves, 2015-2019 | Age (T1) = 11-15 M = 12.5 SD = 0.6 | 1,419 |
| 9 | Summary and discussion | | | |

subsets of the data. The subset selection depended on the availability of data at time of the manuscript preparation and different subsample selections, which yielded longitudinal samples ranging from 543 to 2,109 adolescents. More details regarding the sample characteristics are provided in Table 1.1.

# CHAPTER 2

# VALIDATION OF THE SOCIAL MEDIA DISORDER-SCALE IN ADOLESCENTS: FINDINGS FROM A LARGE-SCALE NATIONALLY REPRESENTATIVE SAMPLE

Maartje Boer, Gonneke W. J. M. Stevens, Catrin Finkenauer, Ina M. Koning, and Regina J. J. M. van den Eijnden

**Author Contributions**

All authors conceived of the study. MB conducted the literature review, data analyses, and drafted the initial and revised manuscript. GS was principal investigator of the data collection. MB assisted with the coordination of the data collection fieldwork. GS, CF, IK, and RvdE critically reviewed all sections of the initial and revised manuscript and advised during all stages of the manuscript preparation. All authors approved of the final manuscript.

**Publication**

Boer, M., Stevens, G. W. J. M., Finkenauer, C., Koning, I. M. , & Van den Eijnden, R. J. J. M. (2021). Validation of the Social Media Disorder-Scale in adolescents: Findings from a large-scale nationally representative sample. *Assessment (in press)*. https://doi.org/10.1177/10731911211027232

# Abstract

Large-scale validation research on instruments measuring problematic social media use (SMU) is scarce. Using a nationally representative sample of 6,626 Dutch adolescents aged 12 to 16, the present study examined the psychometric properties of the nine-item Social Media Disorder-scale. The structural validity was solid, because one underlying factor was identified, with adequate factor loadings. The internal consistency was good, but the test information was most reliable at moderate to high scores on the scale's continuum. The factor structure was measurement invariant across different subpopulations. Three subgroups were identified, distinguished by low, medium, and high probabilities of endorsing the criteria. Higher levels of problematic SMU were associated with higher probabilities of mental, school, and sleep problems, confirming adequate criterion validity. Girls, lower educated adolescents, 15-year-olds, and non-Western adolescents were most likely to report problematic SMU. Given its good psychometric properties, the scale is suitable for research on problematic SMU among adolescents.


*Keywords*: Problematic social media use, social media addiction, adolescents, psychometric properties, validation study.

# Validation of the Social Media Disorder-Scale in Adolescents: Findings from a Large-Scale Nationally Representative Sample

Social network sites and instant messengers such as Instagram and Snapchat have become prominent parts of adolescents' lives (Anderson & Jiang, 2018). The social involvement and entertainment that are associated with social media use (SMU) may enhance adolescents' social capital and feelings of connectedness (Verduyn et al., 2017). However, SMU can become concerning when it is associated with addiction-like symptoms, such as a loss of control over SMU (Griffiths et al., 2014), which we refer to as *problematic SMU*. Research has shown that adolescent problematic social media users are more likely to experience mental health problems (Marino et al., 2018b; Van den Eijnden et al., 2018), have lower school achievements (Al-Menayes, 2015b; Vangeel et al., 2016), and lower sleep quality (Andreassen et al., 2012; Wong et al., 2020). While these studies emphasize the potential threat of problematic SMU to adolescents' development and daily life functioning, validation work on instruments that measure problematic SMU is limited. The present study aims to validate the nine-item Social Media Disorder (SMD) Scale (Van den Eijnden et al., 2016) in a Dutch nationally representative adolescent sample.

There has been debate for many years about whether heavy engagement in activities, for example in SMU, should be regarded as addictive behaviors (Kardefelt-Winther et al., 2017; Van Rooij et al., 2018). For a long time, diagnostic manuals have linked 'addiction' to substance-related disorders only (Potenza, 2014). However, it has been put forward that all addictive behaviors, either related to substances or behaviors, result from similar individual biological and psychosocial processes and share six core criteria of addiction (Griffiths, 2005; Potenza, 2014). These core criteria are: *salience* (i.e., preoccupation: constantly thinking about the activity in concern), *mood modification* (i.e., escape: the activity helps to find relief from negative feelings), *tolerance* (i.e., wanting to engage in the activity more and more), *withdrawal* (i.e., experiencing unpleasant physical or emotional effects when the activity is not possible), *conflict* (i.e., having conflicts at school, work, or with personal close relationships due to the heavy engagement in the activity), and *relapse* (i.e., persistence: being unable to stop or to control the activity) (Griffiths, 2005). With the increasing evidence demonstrating the similarities between substance-related disorders and gambling- and gaming disorders, the latest version of the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) added gambling disorder to the 'substance-related and addictive disorders'-category and internet gaming disorder as a condition requiring further study, whereby both behavioral addictions are defined by the core criteria of addiction and a few additional criteria (American Psychiatric Association, 2013). Unlike gambling and gaming disorder, the DSM-5 does not acknowledge social media disorder as a (tentative) behavioral addiction. However, SMU is a relatively new behavior, that increased especially after the rise of smartphone use around 2012 (Twenge, Martin, et al., 2018), when the development of the DSM-5 was already in progress. It generally it takes several decennia before disorder classification systems acknowledge the existence of new disorders. Scholars argue that people can experience SMU-related addiction symptoms that parallel substance-related addiction symptoms, and that social media addiction results from the same 'biopsychosocial' processes that drive substance-related addictions (Griffiths, 2013; Griffiths et al., 2014; Kuss & Griffiths, 2011). Furthermore, there is increasing evidence that the presence of these symptoms impair adolescents' cognitive and psychosocial functioning (Boer, Stevens, et al., 2020; Boer, Stevens, Finkenauer, De Looze, et al., 2021; Van den Eijnden et al., 2018). In absence of a formal recognition of social media disorder as a behavioral addiction, we refer to it as 'problematic SMU'.

Researchers have used several instruments to measure problematic SMU, but most instruments have not been validated (Andreassen, 2015). To our knowledge, the only instrument that has been validated in a large-scale representative adolescent sample is the Bergen Social Media Addiction Scale (BSMAS) (Andreassen et al., 2016; Bányai et al., 2017; Lin et al., 2017). The BSMAS has been developed parallel to the SMD-scale, and covers the six core criteria of addiction (Griffiths, 2005; Griffiths et al., 2014). Scholars have argued that the presence of addiction criteria in relation to (social media) behaviors is not necessarily indicative of whether the behavior is harmful, which is considered a crucial aspect for defining addiction-like behaviors (Kardefelt-Winther et al., 2017; Van Rooij et al., 2018). Therefore, the SMD-scale measures the same six core criteria of addiction and two additional criteria that refer to harmful implications due to SMU: *problems* (i.e., experiencing problems on important life domains due to SMU) and *displacement* (i.e., displacing social or recreational activities by SMU). The SMD-scale also includes *deception* (i.e., lying about time spent on SMU). These nine criteria for problematic SMU were adopted from the DSM-5 definition of internet gaming disorder (American Psychiatric Association, 2013; Lemmens et al., 2015). By adding three additional criteria to the six core criteria of addiction, the nine-item SMD-scale provides a more comprehensive operationalization of problematic SMU.

The SMD-scale was developed based on a confirmatory factor analysis (CFA) on data from a 27-item questionnaire assessed among 10- to 17-year-old Dutch adolescents, which included three items for each of the nine criteria (Lemmens et al., 2015; Van den Eijnden et al., 2016). The nine-item SMD-scale consists of the items that showed the highest factor loading per criterion. The nine items can be regarded as nine subdimensions, yet together, they intend to reflect one overarching dimension (Van den Eijnden et al., 2016). Indeed, CFA on the nine-item scale demonstrated solid structural validity for a unidimensional (i.e., one-factor) model, with acceptable internal consistency of the test scores. Also, higher scores were associated with higher reports of compulsive internet use, self-declared social media addiction, and mental health problems, indicating good convergent and criterion validity of the test score interpretations (Van den Eijnden et al., 2016). An adapted version of the SMD-scale with polytomous instead of dichotomous response scales was validated among a sample of 553 Turkish adolescents aged 14-18 (Savci et al., 2018). In this study, Exploratory Factor Analysis (EFA) also identified one dimension, and internal consistency of the test scores was acceptable. Also, the convergent and criterion validity of the test score interpretations was adequate (Savci et al., 2018). Although these studies indicated that the SMD-scale has appropriate psychometric properties, important validation steps remain unaddressed.

First, the structural validity of the SMD-scale score interpretations has not been explored in a nationally representative sample. Although the scale aims to measure one overarching dimension problematic SMU (Van den Eijnden et al., 2016), exploring possible multidimensionality is crucial to enhance our understanding of problematic SMU. Furthermore, the use of the sum-score of the nine items to assess adolescents' level of problematic SMU is only justified when the scale measures one underlying dimension to which all nine items substantially contribute. Second, although the test scores of the SMD-scale were found to have acceptable internal consistency (Savci et al., 2018; Van den

Eijnden et al., 2016), the reliability at different levels of problematic SMU has not been investigated. Third, it remains unclear whether the factor structure of the SMD-scale is equal across subpopulations, which is required to reliably compare observed levels of problematic SMU across subpopulations (F. F. Chen, 2007). Because studies suggest that girls, lower-educated adolescents, specific age groups, and immigrant adolescents are more sensitive to developing problematic SMU (Bányai et al., 2017; Ho et al., 2017; Mérelle et al., 2017), it is pivotal to examine whether the scale is measurement invariant across these groups in order to be able to interpret these differences. Fourth, research shows that it is often possible to distinguish subgroups whose members show similar characteristics with regard to a particular behavior (Bányai et al., 2017; Király, Sleczka, et al., 2017; Lemmens et al., 2015; Peeters et al., 2019). It has not been investigated whether the SMD-scale can be used to study subgroups of users, and if so, by which set of criteria these subgroups could be characterized. The identification of such subgroups may provide more insight into the phenomenon of problematic SMU and allow researchers to use the scale to compare subgroups of users on, for example, their wellbeing. Fifth, previously conducted criterion validity analyses on the SMD-scale were limited to assessments of mental health problems (Savci et al., 2018; Van den Eijnden et al., 2016). In order to verify whether the test score interpretations of the scale are valid, associations with other constructs related to adolescents' daily life functioning should be considered as well, including school functioning and sleep problems.

## Current Study

Given the increasing body of literature showing that problematic SMU is negatively associated with mental health and functioning in important life domains, it is essential that research on problematic SMU uses a psychometrically sound instrument. The present study is the first that uses a large-scale, nationally representative sample of adolescents to validate the nine-item SMD-scale. Data came from 6,626 Dutch secondary school adolescents aged 12-16 years who participated in the Health Behavior in School-aged Children study (HBSC). The present study aimed to investigate the (1) structural validity, (2) reliability, (3) measurement invariance, (4) item score patterns, and (5) criterion validity of the SMD-scale scores. After these validation steps, we examined the association between adolescents' demographic characteristics and problematic SMU.



# Methods

## Sample

Analyses were carried out using cross-sectional data from the HBSC-study, conducted in the Netherlands. The study is part of a WHO-collaborative cross-national study carried out every four year since 1983 and investigates adolescents' well-being and health behaviors in their social context. We used the Dutch HBSC-sample collected in 2017 among secondary school students (Stevens et al., 2018). The sample consisted of 6,718 adolescents (51.16% boys) aged 12-16 years ($M_{age}$ = 13.94, $SD_{age}$ = 1.37). The sample comprised different educational levels (46.32% pre-vocational, 25.34% general higher, and 28.34% pre-university) and ethnic backgrounds (78.27% native, 16.59% had at least one parent born in a non-Western country, and 5.15% had at least one parent born in a non-Dutch Western country). Although the sample closely resembled the adolescent population in the Netherlands, the data included sample weights to adjust for sample distribution differences with the population. These weights included gender, educational level, school year, and urbanization degree of participants. The HBSC-sample was therefore nationally representative for the Dutch adolescent population in secondary schools (Van Dorsselaer, 2018). For analytic purposes, the sample was randomly split into two subsamples, which we labelled as 'calibration sample' ($n$ = 3,359) and 'validation sample' ($n$ = 3,359). Respondents who did not respond to any of the items on the SMD-scale were excluded from these samples ($n$ = 92), which yielded a final sample of $n$ = 6,626 ($n_{calibration}$ = 3,310, $n_{validation}$ = 3,316).

The HBSC-data had a hierarchical structure, where adolescents were nested in school classes ($n$ = 328) and schools ($n$ = 85). Schools were randomly selected from a list of schools provided by the Dutch Ministry of Education, after which three to five classes per school (depending on the number of students per school) were randomly selected. The response rate on school-level was 37%. The main reason for not participating was that schools were already approached for other research. School non-response was somewhat higher among schools in urban than in rural areas ($\chi^2(5)$ = 15.6, $p$ < 0.01). Participating and non-participating schools did not differ regarding their average number of students and ethnic composition. There were no refusals on school class level, and on the individual level 92% of all selected adolescents participated. The individual non-response was mostly related to absence from school at the day of survey assessment, due to for example illness or truancy (Van Dorsselaer, 2018).

Participation in the HBSC-study was voluntary and anonymous, conducted through digital self-completion questionnaires during school hours monitored by trained research-assistants. School principals sent information about the study to all parents of adolescents in the selected school classes in advance, and parents were provided the opportunity to refuse participation. Almost all parents provided this passive consent (> 99%). Adolescents gave active consent by ticking a box at the start of the survey that confirmed their approval (> 99%). The study was approved by the ethics council of Social Sciences of Utrecht University (FETC17-079).

## Measures

### *Problematic SMU*

The SMD-scale was used to measure problematic SMU (Van den Eijnden et al., 2016). The scale consists of nine dichotomous items corresponding to the nine diagnostic criteria for internet gaming disorder as stated in the appendix of the DSM-5 (American Psychiatric Association, 2013; Lemmens et al., 2015). The questionnaire was introduced with: “We are interested in your experiences with social media. The term social media refers to social network sites (e.g., Facebook, Twitter, Instagram, Google+, Pinterest) and instant messengers (e.g., WhatsApp, Snapchat, Facebook messenger)”. Subsequently, adolescents were asked “During the past year, have you (…)”, followed by for example “regularly found that you can't think of anything else but the moment that you will be able to use social media again?” (preoccupation). Response options were (1) *yes* and (0) *no*. The items ‘displacement’ and ‘escape’ had slightly different wordings than the initial scale (Van den Eijnden et al., 2016).

### *Mental Health Problems*

Four subscales of the self-report Strength and Difficulties Questionnaire (SDQ) were used to measure mental health problems, including *emotional problems,* *conduct problems, hyperactivity,* and *peer problems* (Goodman et al., 1998). Each subscale consists of five items, for example “I worry a lot” (emotional problems), “I am often accused of lying and cheating” (conduct problems), “I am easily distracted, I find it difficult to concentrate” (hyperactivity), and “Other children or young people pick on me or bully me” (peer problems). Answer categories were (0) *not true*, (1) *somewhat true,* and (2) *certainly true*. Given the ordinal nature of the items, internal consistency of the test scores of each adapted subscale was calculated using the ordinal alpha based on the polychoric correlation matrix (Gadermann et al., 2012). Ordinal alpha was 0.81 for emotional problems, 0.67 for conduct problems, 0.76 for hyperactivity, and 0.64 for peer problems. Our aim was to study the associations between problematic SMU and problematic levels of mental health problems. Therefore, subscale sum-scores were dichotomized in line with recommendations from Goodman and colleagues (1998): Subscale sum-scores higher than the 80$^{th}$ centile were coded as (1) *borderline or abnormal*, whereas subscale sum-scores lower than the 80$^{th}$ centile were coded as (0) *normal*.

### *School Problems*

Adolescents were asked how they feel about school at present, with response ranging from (1) *I like it a lot* to (4) *I don’t like it at all* (Inchley et al., 2016). In order to study associations with particularly school dissatisfaction, the variable was recoded into a dichotomous variable *school dissatisfaction,* with categories (1) *I don’t like it very much/I don’t like it at all* and (0) *I like it a lot/I like it a bit*. Adolescents were also asked whether they feel pressured by the schoolwork they have to do, with responses ranging from (1) *not at all* to (4) *a lot* (Inchley et al., 2016). To study the association between problematic SMU and schoolwork pressure, this variable was dichotomized into the variable *perceived school pressure*, with categories (1) *some/a lot* and (0) *not at all/a little*.

### *Sleep Problems*

Adolescents were asked what time they usually go to bed and what time they usually wake up on schooldays. Answers on these questions were used to establish whether the reported average sleep duration met the age-specific recommendation for daily sleep duration according to the National

Sleep Foundation (Hirshkowitz et al., 2015). For 12- and 13-year-olds, at least nine hours of sleep is recommended, whereas for 14- until 16-year-olds, at least eight hours of sleep is recommended. In order to study the association between problematic SMU and low sleep duration specifically, we created a dichotomous variable *lower sleep duration than recommended*, with categories (1) *not meeting the recommendation* and (0) *meeting the recommendation*. Also sleep quality was measured using five items from the Groningen Sleep Quality Scale (Meijman et al., 2006). Adolescents were asked to evaluate their sleep during the past week on schooldays, for example "I felt like I slept poorly last night". Responses ranged from (1) *never* to (5) *(almost) always*, and therefore high values indicated lower sleep quality. The test scores of the five items yielded a Cronbach's alpha from 0.769. The mean of the five items was dichotomized into the variable *low sleep quality* with categories (1) *mean score above 3.5* and (0) *mean score below 3.5*.

### *Demographic Characteristics*

*Gender* consisted of two categories: (1) *girl* and (0) *boy*. The Dutch education system distinguishes broadly three paths of secondary education: pre-vocational education ('VMBO'), general secondary education ('HAVO'), or pre-university education ('VWO'). Students typically follow one of the three paths. Hence, *educational level* consisted of categories (1) *low* (pre-vocational education, i.e, all 'VMBO' levels or 'VMBO/HAVO'), (2) *medium* (general higher education, i.e., 'HAVO' or 'HAVO/VWO'), and (3) *high* (pre-university education, i.e., 'VWO'). *Age* varied from 12- to 16-year-old. *Ethnic background* was determined by adolescents' responses to the question where their parents were born, and consisted of three categories: *native* (both parents born in the Netherlands), *non-Western* (at least one parent from Africa, Latin-America, Asia (excluding Indonesia and Japan) or Turkey), and *other Western* (at least one parent from Europe (excluding Turkey), North-America, Oceania, Indonesia, or Japan, and no parent from a non-Western country) (Central Bureau for Statistics, 2019b).

## Analysis Strategies

### *Structural Validity*

We explored the number of underlying factors measured by the SMD-scale by conducting an EFA using the calibration sample. A factor should consist of at least three items to be considered as a reliable factor (Costello & Osborne, 2005; Fabrigar et al., 1999). Therefore, with nine items on the scale, we decided a priori that a maximum of three factors should be extracted in the EFA. An oblique (goemin) rotation was applied to interpret the factor loadings, which assumed that factors in the multiple factor solution were correlated. The EFA-factor solutions were evaluated based on the empirical eigenvalues, Horn's parallel analysis, model fit, and quality. The number of factors with *empirical eigenvalues* higher than one indicated the number of factors to extract (Ledesma & Valero-Mora, 2007). *Parallel analysis* evaluated this solution by comparing the empirical eigenvalues with 1000 randomly generated eigenvalues based on the same number of variables and sample size. The number of factors to retain was indicated by the number of factors where the 95$^{th}$ percentile random data eigenvalues did not exceed the empirical eigenvalues (Ledesma & Valero-Mora, 2007). *Model fit* of the factor solution was assessed using the Comparative Fit Index (CFI), Tucker Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR) (Schermelleh-Engel et al., 2003). We did not rely on the $\chi^2$-statistic given its sensitivity to large sample sizes (Fabrigar et al., 1999). *Quality* of the factor solutions was considered poor when removal of items with factor loadings below 0.5 or with cross-loadings that differed by less than 0.2 yielded factors with less than three items (Costello & Osborne, 2005; Howard, 2016). To examine the robustness of the EFA results, we conducted Velicer's minimum average partial (MAP) analysis using the calibration sample. This analysis evaluates multiple factor solutions based on principal component analysis by calculating the average partial correlation between items when the first component is partialled out, when the first two components are partialled out, and so on. The number of factors to retain was indicated by the number of components where the average partial correlation was at its minimum (Velicer, 1976). To examine the robustness and generalizability of the findings from the EFA and MAP analyses, the obtained factor solution was evaluated with a CFA using the validation sample.

### *Reliability and Item Performance*

Given the dichotomous nature of the nine items, reliability of the scores was calculated using the ordinal alpha based on the tetrachoric correlation matrix (Gadermann et al., 2012), which indicates the level of internal consistency. Reliability was further analyzed using Item Response Theory (IRT). IRT models describe the relation between observed item scores and their underlying unobserved latent trait ($\theta$) by means of difficulty (i.e., threshold) and discrimination (i.e., loading) parameters (Baker, 2001). The difficulty parameter of an item indicates at which value of $\theta$ respondents have a 50% probability of endorsing that item. The discrimination parameter of an item denotes the item's ability to discriminate between respondents with high versus low values on the continuum of $\theta$, with higher values suggesting better discrimination (Baker, 2001). The difficulty and discrimination parameters were used to generate information curves, that graphically illustrate the amount of information that was provided by single items and the total scale across the continuum of $\theta$. The higher the information, the higher the reliability (Toland, 2014).

### *Measurement Invariance*

Multigroup CFAs were conducted to examine whether the factor structure of the SMD-scale was measurement invariant across gender, educational level, age, and ethnic background. First, *configural invariance* was modelled by fitting a multigroup CFA where all item loadings and thresholds were freely estimated across groups (e.g., across boys and girls). Second, *scalar invariance* was modelled by fitting a multigroup CFA where item loadings as well as item thresholds were constrained to be equal across groups. The models were estimated according to specific guidelines for invariance testing of dichotomous variables, which do not allow for a separate test of *metric invariance* (i.e., multigroup CFA with equal factor loadings and free thresholds) due to model non-identification (L. K. Muthén & Muthén, 2017c). Measurement invariance was established when adding the equality constraints did not substantially deteriorate model fit in terms of CFI, RMSEA, and SRMR (F. F. Chen, 2007). These fit indices are commonly used in measurement invariance analyses on large samples as an alternative to $\chi^2$-difference tests (F. F. Chen, 2007).

### *Subgroups of Users*

We explored whether we could identify subgroups with specific item score patterns by means of Latent Class Analysis (LCA) on the nine items. Specifically, we evaluated different class (i.e., subgroup) solutions on their model fit and classification accuracy (Nylund et al., 2007). *Model fit* was examined using the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and the Lo-Mendell-Rubin adjusted Likelihood Ratio Test (LMR-LRT). *Classification accuracy* was based on the Entropy. After the best class solution was established, we compared adolescents' observed item scores across the empirically identified classes. In addition, the LCA-models assume by default that the items are independent within each class, that is, that there are no correlations between the residuals of the items (Asparouhov & Muthén, 2015). This assumption of 'conditional independence' is often too restrictive, because it typically does not comply with the data. Therefore, imposing the assumption may lead to biased results and wrong model selection (Uebersax, 1999). Hence, a sensitivity analysis was conducted where the LCA was repeated while allowing for conditional dependence. Particularly, for each model, we consulted the 'bivariate fit information' to inspect the pairs of items that violated the assumption based on the bivariate Pearson Chi-Square (> 10), after which we modified the respective model by adding correlations between the pairs of items that violated the assumption (Asparouhov & Muthén, 2015). We applied this procedure to all class solutions and evaluated whether it yielded a similar model selection as the initial analysis that assumed conditional independence.

### *Criterion Validity*

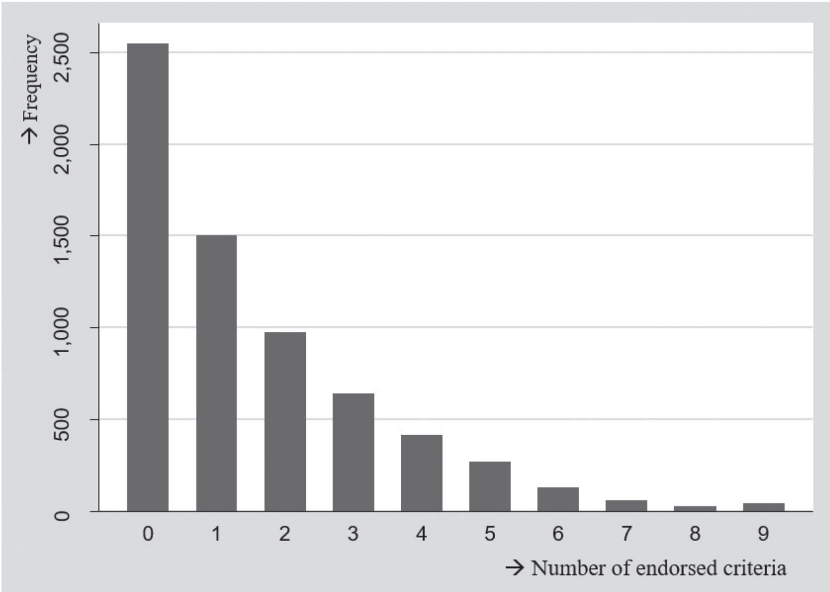
Criterion validity defines the extent to which test scores relate to outcomes they should theoretically be related to. We examined whether higher levels of problematic SMU were associated with more mental health problems (emotional problems, conduct problems, hyperactivity, and peer problems), school problems (school dissatisfaction, school pressure), and sleep problems (less hours of sleep than recommended, low sleep quality). Problematic SMU was measured by the sum-score of the nine items of endorsed problematic SMU criteria (min. 0, max. 9). Due to the dichotomous nature of the outcome variables, analyses were conducted using logistic regression. In these regression analyses, we controlled for gender, educational level, age, and ethnic background. To facilitate interpretability, estimates were transformed into *odds ratios* (ORs) that denote the extent to which the odds of, for example, mental health problems increase with the number of endorsed problematic SMU criteria. Good criterion validity of the test score interpretations was established when a higher number of endorsed criteria was associated with higher probabilities of mental, school, and sleep problems.

***Predictors of Problematic SMU***

Following the validation steps, we examined which demographic characteristics (gender, educational level, age, and ethnic background) predicted a higher number of endorsed problematic SMU criteria. Given that this problematic SMU outcome was considered as a count variable with a high number of zero counts (Figure 2.1), we conducted the analysis using a zero-inflated negative binomial model. We selected this model because it showed better model fit than a zero-inflated Poisson model (chi-bar-square(1) = 428.71, $p$ < 0.001). Furthermore, the zero-inflated negative binomial model showed better fit than an ordinary negative binomial model ($z$ = 3.24, $p$ = < 0.001). The model was interpreted using *incidence rate ratios* (IRRs), which denote, for example, how much higher the number of endorsed problematic SMU criteria is expected to be for girls relative to boys. IRRs were calculated using boys (gender), highly educated adolescents (educational level), 12-year-olds (age), and native adolescents (ethnic background) as the reference categories.

Mplus 8.3 (L. K. Muthén & Muthén, 2017b) was used to conduct the EFA, CFA, and measurement invariance analysis, using Weighted Least Square Means and Variance Adjusted estimation with a probit regression link and theta parameterization. This estimation method was selected because it provided all fit indices for categorical data that were required for model evaluations. The LCA was also conducted using Mplus 8.3, but with Maximum Likelihood estimation with robust standard errors and a logit regression link, as is common for LCA. Stata 14.2 (StataCorp, 2015) was used to conduct Velicer's MAP analysis using the *minap* package (Soldz, 2002). Analyses related to IRT, criterion validity, and associations between demographic characteristics and problematic SMU were also performed with Stata with the default Maximum

**Figure 2.1**
*Distribution of the Number of Endorsed Problematic SMU Criteria, n = 6,609*




*Notes.* SMU = social media use. The number of endorsed problematic SMU criteria was measured with the nine-item Social Media Disorder-Scale.

Likelihood estimation. All analyses were conducted with the sample weight and with a cluster correction on school-class level to correct for the nested structure of the data. All syntax files are publicly available and may be consulted via https://osf.io/pngw5/.

# Results

## Structural Validity

Table 2.1 shows that the EFA on the calibration sample identified one factor with an eigenvalue higher than one (4.572), suggesting a one-factor solution. The parallel analysis showed that only the empirical eigenvalue of the first factor exceeded its 95$^{th}$ random data eigenvalue, which also supports a one-factor solution.

Although the model fits of the one-factor (CFI = 0.984; TLI = 0.979; RMSEA = 0.029; SRMR = 0.049), two-factor (CFI = 0.994; TLI = 0.989; RMSEA = 0.021; SRMR= 0.034), and three-factor (CFI = 1.000; TLI = 1.000; RMSEA < 0.001; SRMR =

**Table 2.1**

*EFA Eigenvalues, Parallel Analysis, and Velicer's MAP Test (Calibration Sample, n = 3,310)*

| Number of factors | Empirical eigenvalues | Parallel test: 95th percentile of random eigenvalues | Velicer's MAP test: Minimum average partial correlation |
|---|---|---|---|
| 0 | -- | -- | 0.196 |
| **1** | **4.572** | **1.103** | **0.027** |
| 2 | 0.819 | 1.070 | 0.048 |
| 3 | 0.746 | 1.048 | 0.071 |
| 4 | 0.630 | 1.028 | 0.127 |
| 5 | 0.599 | 1.010 | 0.222 |
| 6 | 0.562 | 0.995 | 0.314 |
| 7 | 0.456 | 0.978 | 0.461 |
| 8 | 0.349 | 0.960 | 1.000 |

*Notes.* EFA = Exploratory Factor Analysis; MAP = Minimum Average Partial.

0.0.016) solutions were all good, the one-factor solution showed the highest quality (Table 2.2). This is because in the one-factor solution, factor loadings of all items were higher than 0.5, while in the two- and three-factor solutions, there were multiple items with cross-loadings and factor loadings below 0.5. After removal of these items, the factors in the two- and three-factor solutions did not meet the requirement of having at least three items with loadings of 0.5 or higher per factor. Furthermore, the correlations between the factors in the two- and three-factor solutions were high ($r \geq 0.59$), which suggests that the additional factors strongly overlap and should not be considered as separate factors. The EFA obtained one-factor solution was also found by Velicer's MAP test, because the one-factor solution showed the lowest average partial correlation (Table 2.1). The one-factor solution was further evaluated with a CFA using the validation sample. Model fit was good (CFI = 0.983, TLI = 0.977, RMSEA = 0.028, and SRMR = 0.040). Also, the quality of the factor was good, because all nine factor loadings exceeded 0.5 (Table 2.2). The one-factor solution was thus confirmed by the CFA using another, randomly selected sample. These results imply that all nine items contributed to one single dimension.

## Reliability and Item Performance

The ordinal alpha of the one-factor solution was 0.87, which indicates that the internal consistency of the test scores was good. Reliability was further evaluated based on IRT item performance using the two-parameter logistic

**Table 2.2**
*Results EFA and CFA*

| | | Calibration sample (*n* = 3,310) | | | | | | | Validation sample (*n* = 3,316) | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Observed proportion | EFA, rotated factor solutions (*β*) | | | | | | Observed proportion | CFA (*β*) |
| | | | One-factor solution | Two-factor solution | | Three-factor solution | | | | One-factor solution |
| **Criterion** | **During the past year, have you …** | | **Factor 1** | **Factor 1** | **Factor 2** | **Factor 1** | **Factor 2** | **Factor 3** | | |
| Preoccupation | …regularly found that you can't think of anything else but the moment that you will be able to use social media again? | 0.237 | 0.543* | 0.358* | 0.232* | 0.422* | 0.156 | 0.008 | 0.282 | 0.518* |
| Tolerance | …regularly felt dissatisfied because you wanted to spend more time on social media? | 0.083 | 0.729* | 0.604* | 0.204 | 0.835* | -0.073 | 0.020 | 0.084 | 0.729* |
| Withdrawal | …often felt bad when you could not use social media? | 0.173 | 0.697* | 0.833* | -0.003 | 0.928* | 0.008 | -0.183 | 0.178 | 0.711* |
| Persistence | …tried to spend less time on social media, but failed? | 0.274 | 0.559* | 0.079 | 0.501* | -0.069 | 0.699* | 0.001 | 0.235 | 0.607* |
| Displacement | …regularly had no interest in hobbies or other activities because you would rather use social media? | 0.141 | 0.627* | 0.054 | 0.594* | 0.021 | 0.528* | 0.159 | 0.143 | 0.660* |
| Problem | …regularly had arguments with others because of your social media use? | 0.157 | 0.748* | -0.068 | 0.835* | -0.012 | 0.322* | 0.561* | 0.160 | 0.688* |
| Deception | …regularly lied to your parents or friends about the amount of time you spend on social media? | 0.129 | 0.716* | 0.006 | 0.729* | 0.011 | 0.449* | 0.358* | 0.121 | 0.684* |
| Escape | …often used social media so you didn't have to think about unpleasant things? | 0.297 | 0.614* | 0.243* | 0.409* | 0.238 | 0.437* | -0.005 | 0.284 | 0.553* |
| Conflict | …had serious conflict with your parents, brother(s) or sister(s) because of your social media use? | 0.055 | 0.795* | -0.002 | 0.817* | 0.103 | 0.002 | 0.844* | 0.050 | 0.764* |

*Notes.* EFA = Exploratory Factor Analysis; CFA = Confirmatory Factor Analysis. Grey cells depict significant factor loadings at $p < 0.05$.

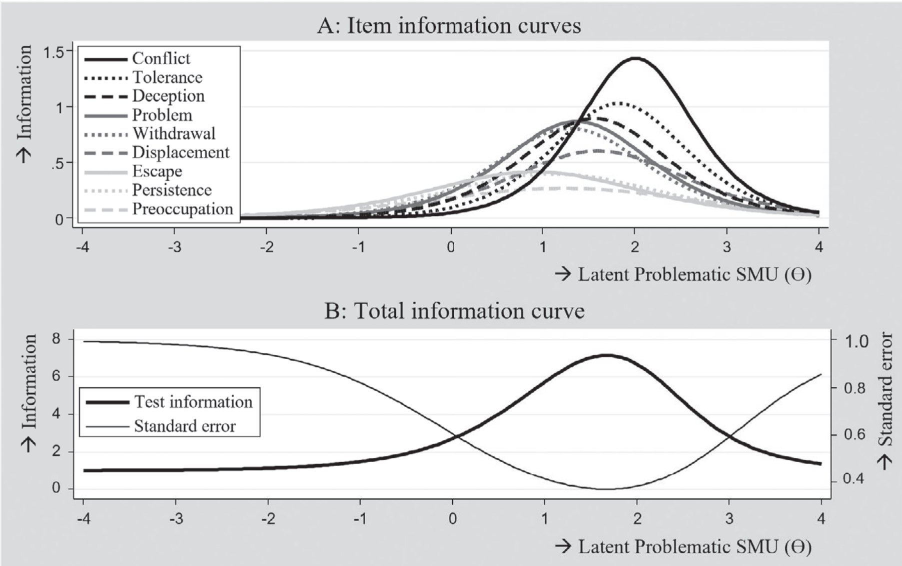
model. The two-parameter logistic model, which allowed the discrimination parameters to vary, was selected because its fit was better than the one-parameter logistic model, which constrained the discrimination parameters to be equal ($\chi^2(8) = 243.67$, $p < 0.001$). IRT models showed that the difficulty parameters of all nine items ranged between 0.91 and 2.01, indicating high difficulty (Baker, 2001). This suggests that the criteria were most likely to be present among adolescents with higher levels of problematic SMU. Discrimination parameters were moderate (1.04 to 1.29; preoccupation, persistence, escape), high (1.55; displacement), or very high (1.80 to 2.40; withdrawal, problem, deception, tolerance, conflict) (Baker, 2001). This implies that the criteria had moderate to very high discriminative power to distinguish adolescents with high from those with low levels of problematic SMU. Figure 2.2A shows that for values at the mean of the latent trait ($\theta$ = 0, corresponding to endorsement of ± one criterion), item 'escape' provided the most information. For values that were one standard deviation above the mean of the latent trait ($\theta$ = 1.00, corresponding to endorsement of ± four criteria), item 'problem' provided the most information. For values two standard deviations above the mean ($\theta$ = 2.00, corresponding to endorsement of ± seven criteria), item 'conflict' provided the most information. Figure 2.2B shows the information function of the total scale. As can be seen, the scale provided most information on higher values of the latent trait, that is, higher than the mean ($\theta$ = 0.00). These findings indicate that test scores were most reliable at moderate to high levels of the scale's continuum. Total information was highest at $\theta$ = 1.68 (corresponding to endorsement of ± six criteria), which indicates that test scores were most reliable at this value.

## Measurement Invariance

The configural multigroup CFAs all showed good model fit (gender: CFI = 0.983; TLI = 0.977; RMSEA = 0.027; SRMR = 0.039, educational level: CFI = 0.984; TLI = 0.978; RMSEA = 0.026; SRMR = 0.047, age category: CFI = 0.982; TLI = 0.975; RMSEA = 0.028; SRMR = 0.049, ethnic background: CFI = 0.983; TLI = 0.977; RMSEA = 0.027; SRMR = 0.042). All group comparisons showed scalar invariance (gender: Δ-CFI = -0.001; Δ-RMSEA = -0.001; Δ-SRMR = 0.001, educational level: Δ-CFI = -0.004; Δ-RMSEA = 0.001; Δ-SRMR = 0.004, age category: Δ-CFI = 0.001; Δ-RMSEA = -0.004; Δ-SRMR = 0.003, ethnic background:

**Figure 2.2**

*Item Information Curves (A) and Total Information Curve (B), n = 6,626*




*Notes.* SMU = social media use. Items in legend were sorted on their discrimination parameter.

Δ-CFI = 0.000; Δ-RMSEA = -0.002; Δ-SRMR = 0.002), because imposing equality constraints did not substantially deteriorate model fits (F. F. Chen, 2007). Thus, the factor loadings and thresholds of all nine items were equal across all group comparisons, which implies measurement invariance across all investigated subpopulations.

## Subgroups of Users

Table 2.3 shows the results of the LCA. We examined five class-solutions, because the five-class solution did not improve model fit relative to the four-class solution (LMR-LRT $p$ = 0.122), which makes estimating additional class-solutions redundant (Nylund et al., 2007). The AIC and BIC decreased with each number of increasing classes, indicating that model fit improved with the number of classes (Nylund et al., 2007). However, the classification accuracy of the four- and five-class solutions was lower than 0.7, which is often considered as unacceptable (Meeus et al., 2010; Reinecke, 2006a). This means that there was substantial overlap in adolescents' item scores between the classes in the four- and five-class solutions, which diminishes the interpretability of the classes (Celeux & Soromenho, 1996). Hence, the two- and three-class solutions were considered more eligible. We selected the three-class solution, which showed a substantial improvement of model fit compared to the two-class solution (ΔAIC = -492.53 and ΔBIC = -424.54).

**Table 2.3**

*Fit Indices and Class Proportions for Five Latent Class Solutions, n = 6,626*

| C. | Par. | AIC | BIC | LMR-LRT *p*-value | Entropy | Class size Class 1 | Class 2 | Class 3 | Class 4 | Class 5 |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 9 | 51973.96 | 52035.14 | | | 100% | | | | |
| 2 | 19 | 47073.14 | 47202.32 | < 0.001 | 0.739 | 73.91% | 26.09% | | | |
| 3 | 29 | 46580.61 | 46777.78 | 0.014 | 0.726 | 61.65% | 34.75% | 3.60% | | |
| 4 | 39 | 46448.72 | 46713.87 | < 0.001 | 0.660 | 57.39% | 29.81% | 11.79% | 1.01% | |
| 5 | 49 | 46378.87 | 46712.00 | 0.122 | 0.674 | 57.39% | 29.84% | 3.53% | 8.18% | 1.06% |

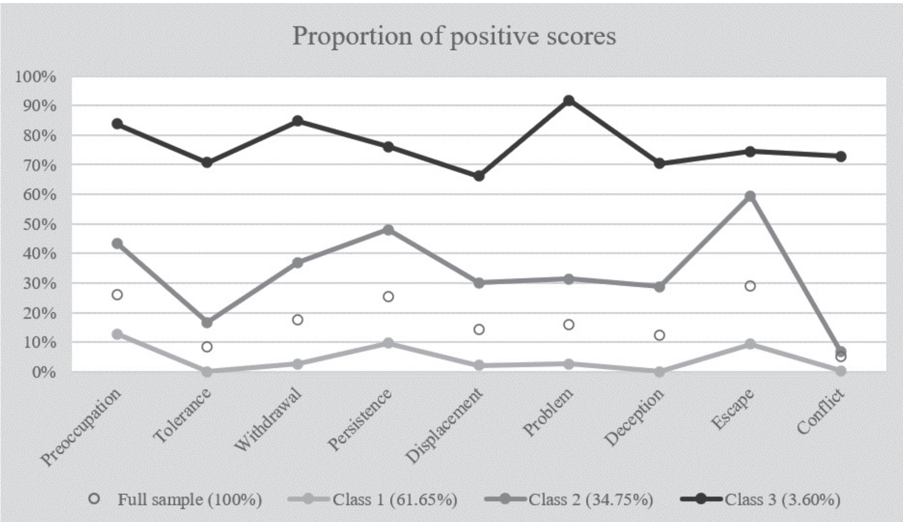
*Notes.* C. = class solution; Par. = number of free parameters; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion; LMR-LRT = Lo-Mendell-Ruben adjusted Likelihood Ratio Test.

A sensitivity analysis was conducted to investigate whether this model selection was robust to conditional dependence of the items. In the one-class solution, 32 out of all 36 possible item correlations were found to be conditionally dependent and specified as such. In the two-class solution, 15 item correlations were specified, and in both the three- and four-class solutions, three item correlations were specified. The LMR-LRT *p*-value of the four-class solution was not significant ($p = 0.74$), and hence no additional classes were estimated. Furthermore, this non-significant finding indicated that the four-class solution did not improve model fit relative to the three-class solution. The three-class solution showed the highest Entropy (0.67), and better model fit in terms of the AIC, BIC, and LMR-LRT *p*-value than the one- and two-class solutions. Hence, the LCA with conditional dependence also favored the three-class solution. Furthermore, the correlation between adolescents' class membership based on the three-class solution with conditional dependence and their class membership based on the three-class solution with conditional independence was 0.95, which suggest that the class assignments with and without the imposed assumption were almost identical. These results imply that the model selection is not biased by conditional dependence of the items.

Figure 2.3 illustrates the proportions of positive scores on the nine criteria per class. In Class 1 (61.65% of the sample), for all nine criteria, the proportions of positive scores were lower than in the full sample. In Class 2 (34.75% of the sample), the proportions of positive scores were higher than in the full sample and Class 1 and ranged between 6.88% ('conflict') and 59.38% ('escape'). In Class 3 (3.60%), the proportions of positive scores were higher than in Class 2 and varied between 66.11% ('displacement') and91.70% ('problem'). Given that the proportions of positive scores on the nine criteria were highest in Class 3, followed by Class 2 and Class 1, respectively, we labeled the three classes as *problematic SMU* (Class 3), *risky SMU* (Class 2), and *normative SMU* (Class 1).

**Figure 2.3**

*Proportion of Positive Scores on the Nine Criteria, by Latent Class, n = 6,626*

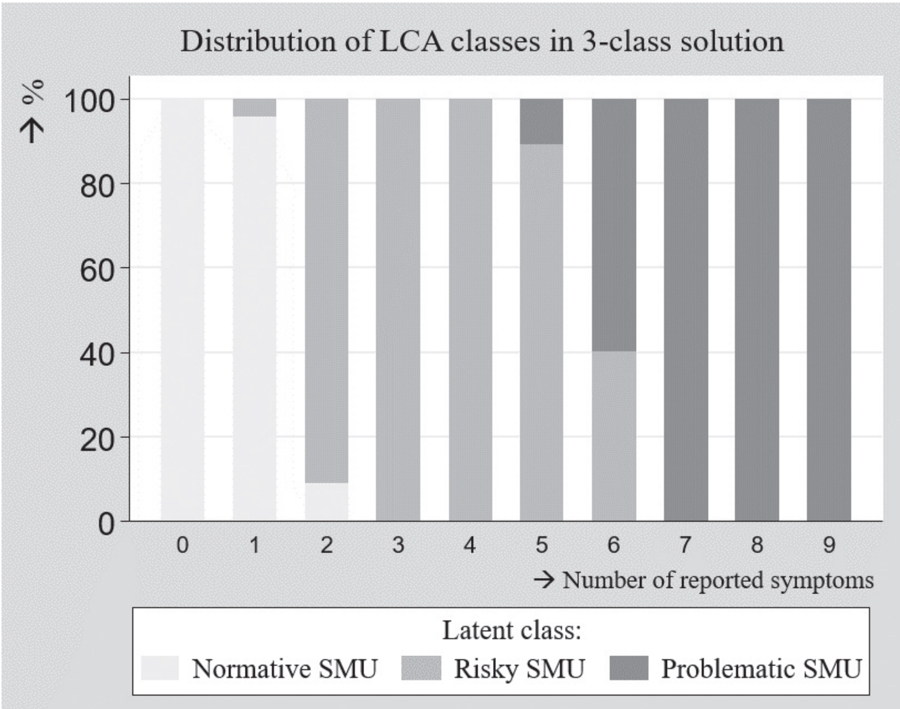



We found that differences in the proportions of endorsed criteria within classes often paralleled the full sample's differences (e.g., 'tolerance' was one of the least endorsed criteria in the full sample and in the three class samples). In other words, we did not observe clear item patterns that distinguished between the three latent classes. Rather, the classes seemed to be distinguished by either high, medium, and low probability of endorsing any of the nine criteria. Therefore, we compared the three classes on adolescents' number of endorsed criteria. Subsequently, we plotted these scores with the latent classes (Figure 2.4). In the problematic SMU class, most adolescents (87.07%) endorsed at least six criteria. In the risky problematic

SMU class, almost all adolescents (95.11%) endorsed two to five criteria. In the normative problematic SMU class, almost all adolescents (97.86%) endorsed not more than one criterion. These results suggest that subgroups may be distinguished by the number of endorsed criteria rather than by the presence of a particular set of criteria or criterion.

**Figure 2.4**

*Distribution of Latent Classes, by the Number of Endorsed Criteria, n = 6,626*




*Note*. SMU = social media use.

## Criterion Validity

Table 2.4 reports the associations between problematic SMU and mental, school, and sleep problems. The higher the number of endorsed criteria, the higher the probability of reporting problems related to mental health, school, and sleep ($OR_{range}$ = 1.18 (low sleep duration) to 1.40 (conduct problems), $p < 0.001$). In separate models, we additionally examined the extent to which subgroups of users reported differences in mental, school, and sleep problems.

**Table 2.4**

*Logistic Regression Results, Problems Related to Mental Health, School, and Sleep, n = 6,626*

| | **Mental health problems** Emotional problems[1] | | | | Conduct problems[2] | | | | Hyperactivity[3] | | | | Peer problems[4] | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *B* | *SE* | *OR* | *M%* | *B* | *SE* | *OR* | *M%* | *B* | *SE* | *OR* | *M%* | *B* | *SE* | *OR* | *M%* |
| Number of endorsed criteria | 0.31*** | 0.02 | 1.36 | 3.99 | 0.34*** | 0.02 | 1.40 | 3.38 | 0.21*** | 0.02 | 1.24 | 2.92 | 0.20*** | 0.02 | 1.22 | 2.10 |
| Normative SMU (max. 1 criterion) | ref. (a) | | | 10.57 | ref. (a) | | | 7.65 | ref. (a) | | | 12.77 | ref. (a) | | | 10.04 |
| Risky SMU (2 to 5 criteria) | 1.03*** (b) | 0.07 | 2.81 | 24.93 | 1.00*** (b) | 0.08 | 2.73 | 18.44 | 0.68*** (b) | 0.06 | 1.98 | 22.51 | 0.49*** (b) | 0.08 | 1.63 | 15.39 |
| Problematic SMU (6 to 9 criteria) | 1.74*** (c) | 0.15 | 5.70 | 40.23 | 2.13*** (c) | 0.16 | 8.44 | 41.13 | 1.34*** (c) | 0.15 | 3.83 | 35.91 | 1.27*** (c) | 0.16 | 3.56 | 28.43 |
| | **School problems** School dissatisfaction[5] | | | | Perceived school pressure[6] | | | | **Sleep problems** Lower sleep duration than recommended[7] | | | | Low sleep quality[8] | | | |
| | *B* | *SE* | *OR* | *M%* | *B* | *SE* | *OR* | *M%* | *B* | *SE* | *OR* | *M%* | *B* | *SE* | *OR* | *M%* |
| Number of endorsed criteria | 0.17*** | 0.02 | 1.19 | 3.10 | 0.24*** | 0.02 | 1.27 | 5.45 | 0.16*** | 0.02 | 1.18 | 3.35 | 0.25*** | 0.02 | 1.28 | 3.93 |
| Normative SMU (max. 1 criterion) | ref. (a) | | | 19.61 | ref. (a) | | | 29.57 | ref. (a) | | | 24.39 | ref. (a) | | | 15.09 |
| Risky SMU (2 to 5 criteria) | 0.50*** (b) | 0.06 | 1.64 | 28.61 | 0.75*** (b) | 0.06 | 2.11 | 46.94 | 0.55*** (b) | 0.06 | 1.73 | 35.76 | 0.78*** (b) | 0.07 | 2.18 | 27.96 |
| Problematic SMU (6 to 9 criteria) | 0.95*** (c) | 0.15 | 2.58 | 38.61 | 1.25*** (c) | 0.14 | 3.48 | 59.38 | 0.90*** (b) | 0.15 | 2.47 | 44.36 | 1.58*** (c) | 0.16 | 4.85 | 46.30 |

*Notes.* SMU = social media use; OR = odds ratios from multivariate logistic regression, controlled for gender, age, education level, and ethnic background; SE = standard error; M% = margin, i.e. expected probability while holding all covariates at their means; Ref. = reference category. Rows with different letters denote significant group differences at $p < 0.05$ with Bonferroni correction.

[1]Borderline / abnormal range of emotional problems (score 5 or higher out of 10).
[2]Borderline / abnormal range of conduct problems (score 4 or higher out of 10).
[3]Borderline / abnormal range of hyperactivity (score 7 or higher out of 10).
[4]Borderline / abnormal range of peer problems (score 4 or higher out of 10).
[5]Does not like school very much or not at all.
[6]Feels some or a lot pressure by schoolwork.
[7]Average sleep duration on weekdays does not meet the age-specific recommendation.
[8]An average score of 3.5 or higher on five items from the Groningen Sleep Quality Scale.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Based on the findings from the LCA (Figure 2.4), we distinguished normative users (endorsement of not more than one criterion), risky users (endorsement of two to five criteria), and problematic users (endorsement of six to nine criteria). Subgroup differences were investigated while controlling for demographic characteristics and with a Bonferroni correction. Results in Table 2.4 show that risky users were more likely to report mental health, school, and sleep problems than normative users ($OR_{range}$ = 1.63 (peer problems) to 2.81 (emotional problems), $p < 0.001$). To an even greater extent, problematic users were more likely to report problems related to mental health, school, and sleep, than normative users ($OR_{range}$ = 2.47 (low sleep duration) to 8.44 (conduct problems), $p < 0.001$). Furthermore, post-hoc pairwise comparisons showed that problematic users had a higher probability of reporting mental health problems, school problems, and low sleep quality than risky users. Problematic and risky users were equally likely to report low sleep duration.

To facilitate interpretability, we transformed odds ratios into *marginal effects* (M), which denote effect sizes in terms of probabilities (Williams, 2012). Table 2.4 shows that for each increase in the number of endorsed criteria, the probability of reporting mental, school, and sleep problems increases with 2.10 (peer problems) to 5.45% (perceived school pressure). The subgroups differed most in emotional and conduct problems: Compared with normative users (10.57% and 7.65%, respectively), risky users were more than twice as likely to report emotional problems and conduct problems (24.93% and 18.44%, respectively), and problematic users were four to five times more likely to report emotional and conduct problems (40.23% and 41.13%, respectively).

In sum, these findings confirm criterion validity of the test score interpretations, because the higher the level of problematic SMU, the higher the probability of problems related to mental health, school, and sleep. Also, as compared to adolescents in the normative SMU-subgroup, adolescents in the problematic SMU subgroup reported more mental health, school, and sleep problems, followed by adolescents in the risky SMU subgroup.

## Predictors of Problematic SMU

Table 2.5 shows the associations between adolescents' demographic characteristics and their number of endorsed problematic SMU criteria ($p$-values were adjusted with Bonferroni corrections). For girls, the number of endorsed criteria was 1.28 times higher than for boys. For lower and medium educated adolescents, the number of endorsed criteria was 1.42 and 1.27 times higher than for higher educated adolescents. Post-hoc pairwise comparisons showed that lower educated adolescents also endorsed more criteria than medium educated adolescents. Compared to 12-year-olds, the number of endorsed criteria was 1.16 times higher for 15-year-olds. Post-hoc pairwise comparisons showed that 12- and 15-year-olds were the only age groups that differed significantly in the number of present criteria. For adolescents with a non-Western immigrant background, the number of endorsed criteria was 1.20 higher than for native adolescents. Post-hoc pairwise comparisons showed no other differences by ethnic background.

In addition, we repeated previous analyses, but used risky and problematic SMU as outcome conducting multinomial regression (using normative SMU as the reference category). Table 2.5 shows that girls and adolescents who attended low or medium education were more likely to report risky SMU and problematic SMU than boys and adolescent who attended high education, respectively. For example, 4.06% of all girls were likely to report problematic SMU, compared to 2.89% of all boys. Compared to 12-year-olds, 13- and 15-year-olds had a higher probability of reporting risky SMU (30.81% vs. 36.98% and 36.67%, respectively). Problematic SMU did not vary significantly by age. Risky SMU did not vary across ethnic background, but non-Western adolescents had a higher probability of reporting problematic SMU compared to native adolescents (5.05% vs. 3.10%).

## Discussion

Using a large-scale, nationally representative sample of Dutch adolescents, the present study demonstrated good psychometric properties for the Social Media Disorder (SMD)-scale (Van den Eijnden et al., 2016), that measures problematic SMU. Multiple assessments of structural validity showed a solid unidimensional factor structure, whereby all nine items substantially contributed to the factor. The test scores showed good internal consistency, but they were most reliable at higher levels of the scale’s continuum. The factor structure was measurement invariant across gender, educational level, age, and ethnic backgrounds. The data yielded three subgroups of users that were distinguished by low, medium, and high proportions of positive scores on all criteria rather than on particular

**Table 2.5**

*Zero-Inflated Negative Binomial and Multinomial Regression, Demographic Characteristics and Problematic SMU, n = 6,626*

| | **Zero-inflated negative binomial** | | | **Multinomial (ref. = normative SMU, max. 1 criterion)** | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Number of endorsed criteria** | | | **Risky SMU (2 to 5 criteria)** | | | | **Problematic SMU (6 to 9 criteria)** | | | |
| | ***B*** | ***SE*** | ***IRR*** | ***B*** | ***SE*** | ***OR*** | ***M%*** | ***B*** | ***SE*** | ***OR*** | ***M%*** |
| *Gender* | | | | | | | | | | | |
| Boys | ref. | | | ref. | | | 28.86 | ref. | | | 2.89 |
| Girls | 0.25*** | 0.03 | 1.28 | 0.58*** | 0.06 | 1.79 | 41.29 | 0.56*** | 0.14 | 1.75 | 4.06 |
| *Educational level* | | | | | | | | | | | |
| High (pre-university) | ref. (a) | | | ref. (a) | | | 30.57 | ref. (a) | | | 1.81 |
| Medium (general higher) | 0.24*** (b) | 0.04 | 1.27 | 0.30** (b) | 0.08 | 1.36 | 36.61 | 0.82** (b) | 0.23 | 2.27 | 3.63 |
| Low (pre-vocational) | 0.35*** (c) | 0.04 | 1.42 | 0.31** (b) | 0.08 | 1.36 | 36.18 | 1.14*** (b) | 0.22 | 3.14 | 4.95 |
| *Age* | | | | | | | | | | | |
| 12 | ref. (a) | | | ref. (a) | | | 30.81 | ref. (a) | | | 2.55 |
| 13 | 0.14 (ab) | 0.05 | 1.15 | 0.29* (b) | 0.09 | 1.34 | 36.98 | 0.36 (a) | 0.22 | 1.43 | 3.27 |
| 14 | 0.14 (ab) | 0.05 | 1.16 | 0.25 (ab) | 0.09 | 1.29 | 35.74 | 0.61 (a) | 0.23 | 1.84 | 4.23 |
| 15 | 0.15* (b) | 0.05 | 1.16 | 0.29* (b) | 0.09 | 1.34 | 36.67 | 0.55 (a) | 0.22 | 1.73 | 3.93 |
| 16 | 0.05 (ab) | 0.05 | 1.05 | 0.12 (ab) | 0.10 | 1.12 | 33.04 | 0.33 (a) | 0.23 | 1.40 | 3.40 |
| *Ethnic background* | | | | | | | | | | | |
| Native | ref. (a) | | | ref. (a) | | | 34.19 | ref. (a) | | | 3.10 |
| Non-Western | 0.19* (b) | 0.04 | 1.20 | 0.14 (a) | 0.08 | 1.15 | 36.63 | 0.56** (b) | 0.17 | 1.75 | 5.05 |
| Other Western | 0.14 (ab) | 0.06 | 1.15 | 0.16 (a) | 0.12 | 1.17 | 36.92 | 0.60 (ab) | 0.29 | 1.82 | 5.20 |

*Notes.* SMU = social media use; SE = standard error; IRR incidence rate ratio; OR = odds ratio; M% = margin, i.e. expected probability while holding all covariates at their means; Ref. = reference category. Rows with different letters denote significant group differences at $p < 0.05$ with Bonferroni correction.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

sets of criteria. These subgroups were labelled as normative, risky, and problematic users, respectively. Further, the criterion validity of the test score interpretations was good: In line with previous research, a higher level of problematic SMU was associated with a higher probability of reporting mental health problems, school problems, and sleep problems. Furthermore, problematic users reported the most mental health, school, and sleep problems, followed by risky and normative users. Girls, low- and medium-educated adolescents, 15-year-olds, and non-Western adolescents endorsed more problematic SMU criteria than boys, high-educated adolescents, 12-year-olds, and native adolescents, respectively.

The finding that the dimensionality assessments identified one underlying factor and that all nine items substantially contributed to the factor implies that the scale measured one construct as intended, and that computing a sum-score from all nine items to assess problematic SMU is valid. It has been argued that some items may identify problematic (social media) behaviors more strongly than others (Kardefelt-Winther et al., 2017). Although the factor loadings of the nine items varied, the small observed differences in their strengths do not support this theory-driven argument. In addition, although the SMD-scale was developed as a unidimensional scale, arguably, a multidimensional factor structure would have been plausible. For example, one may argue that some criteria relate to a behavioral dimension of problematic SMU (e.g., conflict, problem), whereas others to a cognitive (e.g., preoccupation, tolerance). The finding that the unidimensional factor structure was most adequate implies that despite the potential conceptual overlap between particular criteria, together the nine criteria reflect one underlying dimension. However, to consolidate this suggestion, additional exploratory dimensionality tests on data from an extended version of the SMD-scale, that uses more items per criterion (Lemmens et al., 2015; Van den Eijnden et al., 2016), are warranted.

The finding that the factor structure was measurement invariant suggests that the test scores can be used to reliably compare problematic SMU sum-scores across gender, educational levels, age categories, and ethnic backgrounds. This is an important finding since to our knowledge, no previous studies have investigated measurement invariance of any problematic SMU-scale across these four subpopulations using nationally representative data on adolescents. As a result, it remained unclear whether prevalence differences reported in previous research (Bányai et al., 2017; Ho et al., 2017; Mérelle et al., 2017) were biased by varying measurement properties across subpopulations.

The criterion validity analysis showed that the higher the number of endorsed problematic SMU criteria, the higher the probability of reporting problems related to mental health, school functioning, and sleep, confirming good criterion validity of the test score interpretations. Problematic users typically experience unpleasant feelings such as stress or anxiety when SMU is restricted, which may induce mental health problems. Also, the loss of control over SMU may make it difficult to regulate schoolwork responsibilities, which may increase school problems. In addition, being preoccupied with social media or feeling a constant urge to go online may be associated with sleep difficulties. Or conversely, adolescents with problems related to their mental health, school functioning, or sleep may engage in problematic SMU to cope with their problems (Kuss & Griffiths, 2017). Longitudinal research is warranted to examine the directionality of these associations.

In addition, in the criterion validity analysis we also examined the extent to which mental health, school, and sleep problems differed between three subgroups: normative users (endorsement of max. one criterion), risky users (endorsement of two to five criteria), and problematic users (endorsement of six to nine criteria). Although these thresholds for classification were based on observed patterns in the data, research using clinical samples is required to examine whether this classification is justified. Nevertheless, the criterion validity analysis supports the validity of the classification, because the three subgroups differed significantly on mental health, school, and sleep problems, with problematic users being most at risk, followed by risky users and normative users. Furthermore, the finding that risky users were more likely to report problems related to mental health, school, and sleep emphasizes that it is important to study moderate levels of problematic SMU and not only the highest levels, as the presence of a few criteria already seems indicative of problems in several important life domains.

In line with former research (Bányai et al., 2017; Ho et al., 2017; Mérelle et al., 2017), our study showed that the number of endorsed problematic SMU criteria was highest among girls, low-educated adolescents, and non-Western adolescents. In addition, the number of endorsed criteria peaked at 15 years, suggesting that the association between age and problematic SMU was non-linear. This non-linear association may explain why previous research on problematic SMU in adolescents found only a small effect size of age or no age differences at all (Bányai et al., 2017; Ho et al., 2017; Mérelle et al., 2017).

There may be several reasons why girls, lower educated, 15-year-olds, and non-Western adolescents reported higher levels of problematic SMU. Girls may find it more important to maintain and expand social relationships and to express or validate their thoughts and feelings than boys (Kuss & Griffiths, 2011, 2017). This may make girls more vulnerable to developing problematic SMU, as social media facilitates fulfilling these needs (Kuss & Griffiths, 2011, 2017). In addition, Dutch adolescents with a low educational level or with a non-Western background are relatively likely to come from low socioeconomic status families (Central Bureau for Statistics, 2017, 2018a). Adolescents with low socioeconomic status backgrounds are more sensitive to engaging in risky behavior in general than adolescents with high socioeconomic status backgrounds, possibly related to lower support from family, cognitive challenges, or limited self-control (Inchley et al., 2016; Stevens et al., 2018). Similarly, adolescents with a low educational level or with a non-Western background may be more sensitive to developing problematic SMU. Further, the finding that the level of problematic SMU was highest among 15-year-olds implies that there may be an increased risk of problematic SMU during this stage of adolescence. The popularity of social media during adolescence may reach its peak at this age, which may make social media harder to resist. However, empirical research is required to examine the mechanisms underlying the differences found in the present study.

In addition, the observed proportions of positive scores on the problematic SMU criteria were rather low (< 30%). Consequently, the scale's sum-scores showed a skewed distribution, indicating that many adolescents did not endorse any criteria, and a minority endorsed many criteria. This finding suggests that higher levels of problematic SMU are relatively uncommon, which is in line with previously reported prevalence rates of problematic SMU and other problematic internet-related behaviors, including internet gaming disorder and internet addiction (Andreassen, 2015; Kuss et al., 2014; Lemmens et al., 2015). While intense SMU, indicated by very frequent use of social media, is common among contemporary adolescents (Anderson & Jiang, 2018), scholars emphasize that a rather small proportion of social media users may adopt addiction-like behavior regarding their SMU, such as loss of control or interference with daily activities (Griffiths, 2013; Kardefelt-Winther et al., 2017). Hence, the distribution of the sum-scores as observed in the present study supports the validity of the test score interpretations.

## Strengths, Limitations, and Future Directions

This study has important strengths related to the nationally representative character of the data and the number and variety of psychometric tests supporting the reliability and validity of the SMD-scale scores and interpretations. Yet, there are limitations that constitute promising directions for future research. First, the present study used a large sample of Dutch adolescents aged 12–16. To establish the generalizability of our findings in other countries and age groups, research using cross-national assessments of the scale among different age categories is required. For instance, a CFA conducted among a sample of 903 Chinese university students aged 18–23 suggested that the scale measured two factors, with the items problem, deception, and conflict representing a separate factor (Fung, 2019), suggesting that the factor structure may differ across age-groups and/or cultures. Second, the nature of the sample did not allow for clinical validation. Research using clinical samples is required to verify whether the SMD-scale is feasible as a diagnostic tool that accurately identifies problematic users. Third, IRT-analyses showed that the test scores were most reliable for values above the mean of the latent trait, suggesting that the scale provides more precise estimates at higher levels of problematic SMU than at (more common) lower levels of problematic SMU. Hence, the SMD-scale may be most suited to identify moderate to high levels of problematic SMU. This finding is not uncommon for scales that measure exceptional or rare behaviors. For example, validation studies of substance-related disorders and internet gaming disorder scales showed that these scales provide most information at the higher end of the scale's continuum, that is, for scores that exceed the sample mean (Gomez et al., 2019; Martin et al., 2006; Saha et al., 2006). Fourth, adolescents' test scores were based on self-reports, which may deviate from their actual behaviors. For example, adolescents may under- or overestimate the extent to which their SMU impairs important life domains. Comparing parent and adolescent scores on the SMD-scale may provide novel insights into the social reliability of adolescents' self-reports. Fifth, because the data provided one scale that measured problematic SMU, comparison of the psychometric performance of alternative scales was not possible. The SMD-scale distinguishes itself from other scales, such as the BSMAS (Andreassen et al., 2016), by adding the criteria displacement, problems, and deception on top of the six core criteria of addiction. Statistical comparisons of different scales allow researchers to evaluate whether the three additional criteria substantially improve the conceptualization of problematic SMU. Sixth, the criterion validity assessment was limited to measurements related to adolescents' wellbeing. Future studies examining the association between adolescents' intensity of SMU activities and scores on the SMD-scale would extend current knowledge on the validity of the scale. In doing so, the use of objective measures of SMU activities collected through, for example, logged social media data (Marengo et al., 2020; Marino et al., 2017), is considered promising.

## Conclusion

The present study has demonstrated that the SMD-scale has good psychometric properties. Given its solid factor structure, adequate test score reliability, and good validity of the test score interpretations, the scale is suitable for empirical assessments of problematic SMU among adolescents. The scale thereby facilitates future research on adolescent problematic SMU.

# CHAPTER 3

# CROSS-NATIONAL VALIDATION OF THE SOCIAL MEDIA DISORDER-SCALE: FINDINGS FROM ADOLESCENTS FROM 44 COUNTRIES

Maartje Boer, Regina J. J. M. van den Eijnden, Catrin Finkenauer, Meyran Boniel-Nissim, Claudia Marino, Jo Inchley, Alina Cosma, Leena Paakkari, and Gonneke W.J.M. Stevens

**Author Contributions**

MB, RvdE, CF, and GS conceived of the study. MB conducted the literature review, data analyses, and drafted the majority of the initial and revised manuscript. CM and AC drafted parts of the methods and discussion section. GS, RvdE, and CF advised during all stages of preparing and revising the manuscript. JI was the international coordinator of the HBSC study. All authors critically reviewed the initial and reviewed manuscript, and approved of the final manuscript.

**Publication**

Boer, M., Van den Eijnden, R. J. J. M., Finkenauer, C., Boniel-Nissim, M., Marino, C., Inchley, J., Cosma, A., Paakkari, L., & Stevens, G. W. J. M. (2022). Cross-national validation of the Social Media Disorder-Scale: Findings from adolescents from 44 countries. *Addiction, 117*(3), 784-795. https://doi.org/10.1111/add.15709

# Abstract

There is currently no cross-national validation of a scale that measures problematic social media use (SMU). The present study investigated and compared the psychometric properties of the Social Media Disorder (SMD)-scale among young adolescents. Data came from 222,532 adolescents from 44 countries participating in the Health Behaviour in School-aged Children (HBSC) survey (2017/2018). The HBSC survey was conducted in the European region and Canada. Participants were on average 13.5 years old ($SD$ = 1.6) and 51.2% were girls. Problematic SMU was measured using the 9-item SMD-scale with dichotomous response options. Confirmatory factor analyses (CFA) showed good model fit for a one-factor model across all countries (min. comparative fit index (CFI) and Tucker–Lewis index (TLI): 0.963 and 0.951, max. root mean square error of approximation (RMSEA) and standardized root mean square residual (SRMR): 0.057 and 0.060), confirming structural validity. The internal consistency of the items was adequate in all countries (min. alpha = 0.840), indicating that the scale provides reliable scores. Multigroup CFA showed that the factor structure was measurement invariant across countries (ΔCFI = -0.010, ΔRMSEA = 0.003), suggesting that adolescents' level of problematic SMU can be reliably compared cross-nationally. In all countries, gender and socioeconomic invariance was established, and age invariance was found in 43 out of 44 countries. In line with prior research, in almost all countries, problematic SMU related to poorer mental wellbeing (range $\beta_{STDY}$ = 0.193 to 0.924, $p$ < 0.05) and higher intensity of online communication (range $\beta_{STDY}$ = 0.163 to 0.635, $p$ < 0.05), confirming appropriate criterion validity. The SMD-scale appears to be suitable for measuring and comparing problematic social media use among young adolescents across many national contexts.


*Keywords*: Problematic social media use, social media addiction, international validation, psychometric tests, adolescents, HBSC.

# Cross-national Validation of the Social Media Disorder-Scale: Findings from Adolescents from 44 Countries



Adolescents are the most digitally connected age group worldwide (Unicef, 2017). Research among European adolescents shows that between 2017 and 2019, 77% of 15- and 16-year-olds reported daily use of social media (Smahel et al., 2020), such as Instagram and Snapchat. However, concerns have been raised about adolescents who display symptoms of addiction regarding social media use (SMU) (La Barbera et al., 2009), such as being unable to control SMU, or by displacing other activities such as hobbies and sports for SMU (Griffiths et al., 2014; Van den Eijnden et al., 2016). However, diagnostic manuals, such as the Diagnostic and Statistical Manual of Mental Disorders (DSM-5), do not acknowledge social media addiction. Therefore, we refer to addiction-like SMU as *problematic SMU*. Cross-national data from the present Health Behaviour in School-aged Children (HBSC) study shows that, in 2017 and 2018, 4 to 18% of 15-year-olds reported problematic SMU (Inchley et al., 2020b).

With an increasing body of evidence suggesting that problematic SMU threatens different aspects of adolescents' wellbeing (Boer, Stevens, et al., 2020; Boer, Stevens, Finkenauer, De Looze, et al., 2021; Marino et al., 2018b; Piteo & Ward, 2020), different scales that measure problematic SMU have been developed. One of the most widely adopted scales is the Bergen Social Media Addiction Scale (Andreassen et al., 2016), which covers six items that parallel the core criteria of addiction, including preoccupation (i.e., salience), tolerance, withdrawal, persistence (i.e., relapse), escape (i.e., mood modification), and conflict (Griffiths, 2005; Griffiths et al., 2014). However, this conceptualization may not sufficiently measure the detrimental impact of this behavior for daily life, which is considered one of the core aspects of addiction-like behaviors (Kardefelt-Winther et al., 2017; Van Rooij et al., 2018). Another scale that measures problematic SMU is the nine-item Social Media Disorder (SMD)-scale (Boer, Stevens, Finkenauer, Koning, et al., 2021; Van den Eijnden et al., 2016). This scale includes the six core criteria and two additional criteria that measure detrimental consequences due to SMU, namely *problems* in important life domains and *displacement* of activities. In addition, it also includes the criterion *deception*. Together, these nine criteria parallel the criteria for internet gaming disorder as listed in the appendix of the DSM-5 (American Psychiatric Association, 2013; Lemmens et al., 2015). By including three additional criteria on top of the six core criteria, the SMD-scale measures problematic SMU in a way that corresponds more with the scholarly and clinical definition of behavioral addictions, thereby possibly advancing the measurement of problematic SMU.

To our knowledge, validation studies on problematic SMU-scales remain limited to single-country data (Al-Menayes, 2015a; Andreassen et al., 2012; Bányai et al., 2017; Lin et al., 2017; Monacis et al., 2017; Phanasathit et al., 2015; Pontes et al., 2016; Şahin, 2018), including validation studies on the SMD-scale (Boer, Stevens, Finkenauer, Koning, et al., 2021; Savci et al., 2018; Van den Eijnden et al., 2016; Watson et al., 2020). Studies among Dutch secondary school adolescents showed that the SMD-scale had a solid unidimensional factor structure and adequate internal consistency. Also, higher values on the scale were associated with higher levels of impulsive internet use, self-declared social media addiction, and problems related to mental health, sleep, and school functioning, confirming convergent and criterion validity (Boer, Stevens, Finkenauer, Koning, et al., 2021; Van den Eijnden et al., 2016). Research among U.S. adolescents aged 13 to 19 years old showed that the scale scores provided good internal consistency and correlated strongly with scores on alternative problematic SMU scales (Watson et al., 2020). A study among Turkish adolescents aged 14 to 18 years old used an adapted version of the SMD-scale with polytomous response scales and showed adequate internal consistency and structural validity for a unidimensional scale (Savci et al., 2018).

Although these single-country validation studies suggest that the SMD-scale has appropriate psychometric properties across some national contexts, these studies used different analyses and sample characteristics were diverse (e.g., with respect to age and representativeness), limiting the comparability of their findings. Adolescents' problematic SMU can only be compared cross-nationally if it is measured with the same scale, which has been shown to be reliable and valid using identical analyses on comparable national samples. Furthermore, to secure comparability, the measurement properties should be invariant across countries to confirm that adolescents from different countries interpret the questions of the scale in a similar manner (Davidov, 2010; Van de Schoot et al., 2012). Cross-national research on problematic SMU is important to identify countries with particularly high levels of problematic SMU and to inform preventive actions to address the possible detrimental outcomes of problematic SMU (Boer, Stevens, et al., 2020; Boer, Stevens, Finkenauer, De Looze, et al., 2021; Marino et al., 2018b; Piteo & Ward, 2020). Furthermore, international validation of a problematic SMU-scale is crucial for obtaining more robust global knowledge about problematic SMU and identifying the extent to which it imposes a risk to adolescents' health worldwide.



### Current Study

In response to the lack of cross-national validation of problematic SMU-scales, the present study aimed to investigate the psychometric properties of the SMD-scale using nationally representative cross-national data from the HBSC study. We examined the structural validity, reliability, measurement invariance, and criterion validity of the scale. Thereby, we aim to establish whether the scale is suitable to measure and compare adolescent problematic SMU within a broad international context.

## Methods

### Sample

The HBSC study is a cross-sectional study that has been conducted every four years since 1983 in collaboration with the WHO Regional Office for Europe. The study monitors the health (behaviors) of 11-, 13-, and 15-year-olds. The present study uses the 2017/2018 survey, which includes nationally representative data from 47 countries and regions from the European Region and Canada. More specifically, it includes data from 45 countries and two regional subsamples for Belgium (Flanders and Wallonia). For consistency, we refer to the subsamples as countries. To ensure semantic equivalence across different languages and cultural settings, questionnaires were translated following a standardized protocol (Inchley et al., 2018). National research teams translated the English questionnaire into their national language and back-translated it into English, after which these translations were verified and corrected by language experts from the HBSC network (Inchley et al., 2018; Roberts et al., 2007). All countries strictly followed the sampling method and data collection procedures as prescribed by the HBSC international research protocol, which involved sampling via randomly selected schools and classes (Inchley et al., 2018). Surveys were administered in classroom settings during school hours through digital (45%) or paper-and-pencil (55%) self-completion. Respondents were informed that participation was voluntary and anonymous. Active informed consent was obtained from schools and participants. Depending on the country, passive or active informed consent was obtained from parents. Participating countries obtained ethical approval of the study procedures from their institutional ethics committee (Inchley et al., 2018).

## Measures

### *Problematic SMU*

Problematic SMU was assessed with the 9-item SMD-scale (Van den Eijnden et al., 2016). The questions were introduced with 'We are interested in your experiences with social media. The term social media refers to social network sites (e.g., Facebook, [add other local examples]) and instant messengers (e.g., [insert local examples], WhatsApp, Snapchat, Facebook messenger).' Subsequently, respondents were asked 'During the past year, have you…', followed by, for example, 'regularly found that you can't think of anything else but the moment that you will be able to use social media again?' (preoccupation), with answer options 1 *yes* and 0 *no*. All items can be found in the Appendix (Table A3.1). For the criterion validity analyses, the sum-score of the scale was dichotomized, whereby adolescents reporting six to nine present symptoms were defined as a problematic user (1 *problematic user: 6-9 symptoms,* 0 *non-problematic user: 0-5 symptoms*) (Boer, Stevens, Finkenauer, Koning, et al., 2021; Boer, Van den Eijnden, et al., 2020). This definition is based on a latent class analysis on the nine items in a nationally representative sample of Dutch adolescents aged 12-16, which identified three subgroups of users, whereby adolescents in the subgroup with the highest levels of problematic SMU reported six or more symptoms (Boer, Stevens, Finkenauer, Koning, et al., 2021).

### *Mental Wellbeing*

We assessed two indicators of mental wellbeing. *Life satisfaction* was measured using the Cantril ladder, where respondents rated their life on a scale, ranging from 0 *worst possible life* to 10 *best possible life* (Cantril, 1965). This measure has shown good test-retest reliability and (cross-national) convergent validity with other mental wellbeing measures (Casas & Rees, 2015; Levin & Currie, 2014; Mazur et al., 2018). *Psychosomatic complaints* were measured using the 8-item HBSC Symptom Checklist (Haugland & Wold, 2001). Respondents were asked how often in the past six months they had experienced, for example, feeling low (psychological complaint), or headache (somatic complaint), with answer options ranging from 1 *about every day* to 5 *rarely or never*. A mean score was computed after scores were rescaled, such that high scores indicate high levels of psychosomatic complaints (range: 1-5). Validation studies on the 8-item measure have shown adequate test-retest reliability, good content validity, and high factor loadings (> 0.50) across different national settings (Haugland & Wold, 2001; Ravens-Sieberer et al., 2008).

### *Intensity of Online Communication*

A newly developed 4-item measure, adapted from the EU Kids Online Survey on the frequency of online communication with different contacts (Mascheroni & Ólafsson, 2014), was used. Respondents were asked how often they have online contact through social media with close friends, friends from a larger friend group, friends they met through internet, and other people (e.g., parents, siblings, classmates, teachers). Answer options ranged from 1 *never/almost never* to 5 *almost all the time throughout the day,* and a *don't know/doesn't apply* option. The intensity of online communication was defined by the maximum score of the four items. Hence, higher scores indicate higher intensity of online communication (range: 1-5).

### *Demographic Characteristics*

*Gender* was assessed by asking respondents whether they are boy or girl (1 *girl*, 0 *boy*). *Age* was computed based on the respondent's month and year of birth and the date of the survey assessment. For the measurement invariance analysis, respondents were assigned to three categories: 11- (≥*10 and* ≤ *12.5*), 13- (>*12.5 and* ≤ *14.5*), and 15-year-olds (>*14.5 and* ≤ *16.5*). *Socioeconomic status* was measured with the 6-item Family Affluence Scale (FAS) (Currie et al., 2008), which assesses material assets in the household (e.g., number of cars).

Sum-scores were computed and transformed into proportional ranks given their residential country (Elgar et al., 2017), and subsequently divided in three categories (1 *lowest 20%*, 2 *middle 60%*, and 3 *highest 20%*).

## Analyses

### *Missing Data*

Missing data on the study variables were imputed based on multiple imputation with chained equations (Royston & White, 2011). Five imputations were generated using predictive mean matching with five 'nearest neighbors' and logistic regression for the dichotomous items, predicted by the available data on the study measures, demographic characteristics, other wellbeing indicators, and residential country to control for the nested structure of the data.

### *Structural Validity*

The structural validity defines the extent to which the scores on the scale reflect the underlying dimension. The SMD-scale was developed as a unidimensional scale (Boer, Stevens, Finkenauer, Koning, et al., 2021; Van den Eijnden et al., 2016). Hence, we evaluated the factor structure of the scale based on CFA of a one-factor model, based on the Comparative Fit Index (CFI), Tucker Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR) (CFI/TLI: ≥ 0.9 acceptable, ≥ 0.95 good; RMSEA: ≤ 0.08 acceptable, ≤ 0.06 good; SRMR: ≤ 0.10 acceptable, ≤ 0.08 good) (Hu & Bentler, 1999). We did not rely on the Chi-square statistic given its sensitivity to large sample sizes (Fabrigar et al., 1999). Solid structural validity was established when the model fit was acceptable and at least five items had factor loadings of 0.50 or higher (Costello & Osborne, 2005). Prior to the CFA, we conducted Exploratory Factor Analysis (EFA) for each country to consolidate the proposition that the SMD-scale measures one underlying dimension (Boer, Stevens, Finkenauer, Koning, et al., 2021; Van den Eijnden et al., 2016). The EFA and CFA were conducted on different random subsamples, referring to calibration (EFA) and validation (CFA) subsamples.

### *Reliability*

Reliability was assessed based on the internal consistency of the scores on the nine items using the validation subsamples. Given the dichotomous nature of the nine items, we computed the internal consistency using the tetrachoric correlation matrix, referred to as the ordinal alpha (Gadermann et al., 2012). An alpha of 0.80 or higher indicates good reliability (Gadermann et al., 2012).

### *Measurement Invariance*

Measurement invariance means that the scale measures the same underlying construct across subpopulations, which is required in order to reliably compare the level of problematic SMU across subpopulations (Van de Schoot et al., 2012). To do so, we examined whether the factor structure was comparable across countries (44 countries), gender (boy and girl), age groups (11-, 13-, and 15-year-olds), and socioeconomic status (low, middle, and high family affluence) using multigroup CFA. We compared the model fit of a multigroup CFA where all item factor loadings and thresholds were free to vary across countries or subgroups (i.e., *configural invariance*) with the model fit of a multigroup CFA where all item factor loadings and thresholds were constrained to be equal across all countries or subgroups (i.e., *scalar invariance*) using the default model settings (L. K. Muthén & Muthén, 2017c). A test of loading invariance where thresholds are freely estimated (i.e., *metric invariance*) was not conducted because this model is not identified when using dichotomous items (L. K. Muthén & Muthén, 2017c). Measurement invariance was established when the scalar model decreased CFI by not more than 0.010 and increased RMSEA by not more than 0.015, relative to the configural model (F. F. Chen, 2007; Cheung & Rensvold, 2002).

### *Criterion Validity*

Criterion validity refers to the extent to which a construct relates to another construct that it should theoretically be related to. Research suggests that problematic SMU impairs mental health (Boer, Stevens, Finkenauer, De Looze, et al., 2021; Raudsepp, 2019), and that problematic users also use online communication intensively (Frost & Rickwood, 2017; Marino et al., 2018a). Accordingly, review studies show a small to moderate negative association between problematic SMU and positive mental wellbeing, such as life satisfaction, and a positive moderate association between problematic SMU and negative mental wellbeing, such as depression (Huang, 2020; Marino et al., 2018b). Review studies on problematic SMU and the frequency or time spent on SMU (including activities such as browsing, chatting) show a small to moderate association (Frost & Rickwood, 2017; Parry et al., 2020), which may also apply to the relation between problematic SMU and online communication intensity. Hence, appropriate criterion validity would be established when problematic SMU was negatively related to life satisfaction with small to moderate effect size, positively to psychosomatic complaints with moderate effect size, and positively to the intensity of online communication with small to moderate effect size ($p < 0.05$). Associations were examined using linear regression where problematic SMU predicted life satisfaction, psychosomatic complaints, and online communication, while controlling for gender, age, and socioeconomic status. Estimates of problematic SMU were standardized to interpret their effect size. As the problematic SMU scores were dichotomous, estimates were STDY-standardized (0.2 = small, 0.5 = moderate, 0.8 = large effect size) (Cohen, 1988; L. K. Muthén & Muthén, 2017a).

### *Technical Details*

Missing data were imputed using Stata 13.0 (StataCorp, 2013). Analyses were conducted on the imputed datasets with Mplus 8.5 (L. K. Muthén & Muthén, 2017b). The CFAs, internal consistency, and measurement invariance analyses were conducted using Weighted Least Square Means and Variance Adjusted (WLSMV) estimation with a probit regression link, as appropriate for analyses with categorical outcomes (Rhemtulla et al., 2012). Regression analyses from the criterion validity analysis were conducted with Maximum Likelihood with Robust standard errors (MLR). In all analyses, standard errors were corrected for clustering of adolescents within schools or classes. For some countries, the analyses were conducted using sample weights to adjust for sample distribution differences with the respective population. Analyses by country were conducted with the *MplusAutomation*-package in RStudio 1.2.5042 (Hallquist & Wiley, 2018; RStudio Team, 2021). All codes related to the analyses may be consulted via https://osf.io/bgkec/. The analyses were not pre-registered and therefore, results should be considered exploratory.

# Results

## Sample Characteristics

The initial sample includes 47 countries (*n* = 244,097). Three countries were excluded because they did not survey problematic SMU (*n* = 10,576). Adolescents who responded '*not applicable/don't know*' to all items of the intensity of online communication scale automatically skipped the questions on problematic SMU and were also excluded from the sample (ranging from 1.78% in North Macedonia to 17.62% in Azerbaijan, *n* = 10,989). This yielded a sample of 222,532 adolescents from 44 countries (listed in the tables from the Appendix). From these countries, the average school and participant response rates were 69.70% and 80.34%, respectively (Inchley et al., 2020a). Adolescents were on average 13.54 years old (*SD* = 1.63, min. = 10.00, max. = 16.50) and 51.24% were girls.

Cronbach's alpha for psychosomatic complaints was 0.81, which indicates good reliability (Gadermann et al., 2012). Cronbach's alpha was not calculated for the other study measures, because they either consisted of one item (life satisfaction) or were considered as a formative scale (intensity of online communication, socioeconomic status), which means that not all items were expected to have high intercorrelations (Bollen & Lennox, 1991).

Missing data on the study measures ranged between 0.65% (age) and 10.14% (problematic SMU: escape). Little's Chi-square test for missing data showed that these data were not completely missing at random (Chi-square(55,103) = 82,498.58, $p < 0.001$), which implies that imputation of missing data is required in order to prevent potential bias (Enders & Bandalos, 2001).

## Prevalence Differences

Table 3.1 shows that the most prevalent symptoms were 'persistence' (30.66%) and 'escape' (30.74%). The least prevalent symptoms were 'conflict' (14.38%) and 'deception' (14.56%).

Figure 3.1 shows that over a third of adolescents did not report symptoms, whereas 7.64% reported problematic SMU, that is, six or more symptoms. By country, problematic SMU ranged between 3.20% (Netherlands) and 16.41% (Malta). All prevalence rates of problematic SMU (symptoms) by country can be found in the Appendix (Table A3.2).

**Table 3.1**

*Prevalence Problematic SMU Symptoms (n = 222,532 in 44 Countries)*

| During the past year, have you... | Item | % | Min. %[1] | Max. %[2] |
|---|---|---|---|---|
| ...regularly found that you can't think of anything else but the moment that you will be able to use social media again? | Preoccupation | 22.07% | 14.16% | 34.73% |
| ...regularly felt dissatisfied because you wanted to spend more time on social media? | Tolerance | 18.89% | 7.33% | 35.34% |
| ...often felt bad when you could not use social media? | Withdrawal | 21.30% | 11.63% | 48.21% |
| ...tried to spend less time on social media, but failed? | Persistence | 30.66% | 22.46% | 42.10% |
| ...regularly neglected other activities (e.g., hobbies, sport) because you wanted to use social media? | Displacement | 15.73% | 7.03% | 26.13% |
| ...regularly had arguments with others because of your social media use? | Problem | 18.86% | 11.87% | 39.64% |
| ...regularly lied to your parents or friends about the amount of time you spend on social media? | Deception | 14.56% | 8.76% | 26.75% |
| ...often used social media to escape from negative feelings? | Escape | 30.74% | 11.42% | 47.02% |
| ...had serious conflict with your parents, brother(s) or sister(s) because of your social media use? | Conflict | 14.38% | 4.67% | 32.23% |
| **Problematic SMU (six or more symptoms)** | | 7.64% | 3.20% | 16.41% |

*Note*. SMU = social media use.

[1] Lowest observed prevalence across all 44 countries.

[2] Highest observed prevalence across all 44 countries.

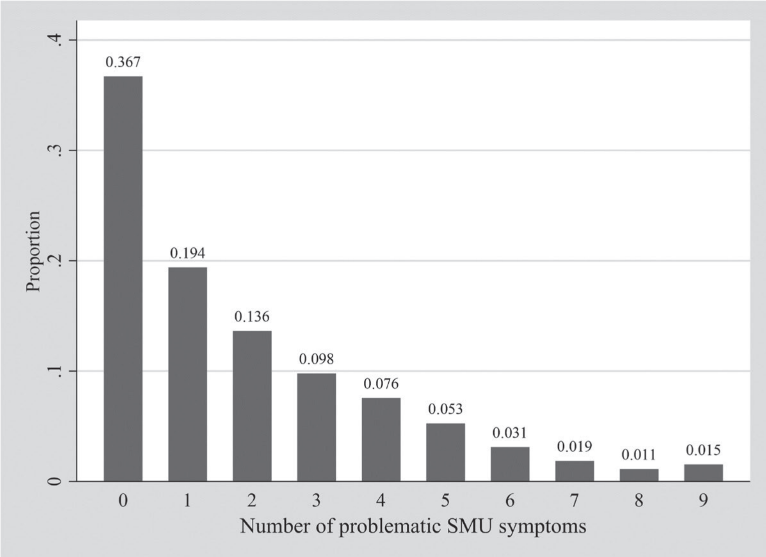
Multivariate logistic regressions were conducted to investigate whether problematic SMU differed by survey mode, gender, age, and socioeconomic status within each country. In none of the countries, problematic SMU differed by survey mode (Table 3.2). In multiple countries, gender, age, and socioeconomic status were associated with problematic SMU, although the direction of these associations was not consistent.

## Structural Validity

As a preliminary step, EFAs were conducted prior to the CFAs. Details regarding the EFAs can be found in the Appendix (Tables A3.3 and A3.4). Overall, 34 out of 44 countries consistently showed that a one-factor model was preferred over a two- and three-factor model. In the 10 other countries, findings were inconsistent. However, the model fit of the one-factor model was good in all countries, as well as the quality of the factor. Thus, we consider the factor structure as unidimensional. As such, testing a one-factor model using CFA was considered justified.

**Figure 3.1**

*Distribution of the Sum-Score of the Social Media Disorder-Scale, Pooled Sample, n = 222,532.*




*Note.* SMU = social media use.

**Table 3.2**

*Multivariate Logistic Regression, Problematic SMU (n = 222,532 in 44 Countries)*

| | **Pooled sample** | | | **Analyses by country** | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | ***B*** | ***SE*** | **OR** | **Countries positive** | **Min. OR[1]** | **Max. OR[1]** | **Countries negative** | **Min. OR[2]** | **Max. OR[2]** |
| *Survey mode (ref. = paper and pencil self-completion)*[3] | | | | | | | | | |
| Digital self-completion | -0.026 | 0.024 | 0.974 | 0 | | | 0 | | |
| *Gender (ref. = boy)* | | | | | | | | | |
| Girl | 0.189*** | 0.019 | 1.208 | 19 | 1.326 | 1.853 | 4 | 0.475 | 0.779 |
| *Age (ref. = 11-year-old)* | | | | | | | | | |
| 13-year-old | 0.394*** | 0.028 | 1.484 | 27 | 1.395 | 3.225 | 1 | 0.215 | 0.215 |
| 15-year-old | 0.477*** | 0.029 | 1.612 | 28 | 1.470 | 3.238 | 1 | 0.341 | 0.341 |
| *Socioeconomic status (ref. = low)* | | | | | | | | | |
| Middle | -0.100*** | 0.023 | 0.905 | 1 | 2.939 | 2.939 | 4 | 0.576 | 0.683 |
| High | -0.023 | 0.028 | 0.977 | 1 | 1.547 | 1.547 | 5 | 0.503 | 0.682 |

*Notes.* SMU = social media use; *B* = logit coefficient; *SE* = standard error; *p* = p-value; OR = odds ratio; ref. = reference category; problematic SMU was defined by reporting six to nine problematic SMU criteria.
[1] Minimum/maximum value of the OR across countries where a positive association was found ($p < 0.05$).
[2] Minimum/maximum value of the OR across countries where a negative association was found ($p < 0.05$).
[3] The association between survey mode and problematic SMU was estimated across eight out of 44 countries ($n = 43{,}802$), because there were only eight countries where both survey modes were employed.
*** = $p < 0.001$.

**Table 3.3**

*Summary CFA Results, Validation Samples, by Country (n = 111,278 in 44 Countries)*

| During the past year, have you… | Item | Min. loading[1] | Max. loading[2] | Average loading[3] |
|---|---|---|---|---|
| …regularly found that you can't think of anything else but the moment that you will be able to use social media again? | Preoccupation | 0.524 | 0.805 | 0.709 |
| …regularly felt dissatisfied because you wanted to spend more time on social media? | Tolerance | 0.630 | 0.857 | 0.743 |
| …often felt bad when you could not use social media? | Withdrawal | 0.604 | 0.851 | 0.733 |
| …tried to spend less time on social media, but failed? | Persistence | 0.380 | 0.814 | 0.566 |
| …regularly neglected other activities (e.g., hobbies, sport) because you wanted to use social media? | Displacement | 0.509 | 0.838 | 0.654 |
| …regularly had arguments with others because of your social media use? | Problem | 0.470 | 0.873 | 0.718 |
| …regularly lied to your parents or friends about the amount of time you spend on social media? | Deception | 0.589 | 0.859 | 0.738 |
| …often used social media to escape from negative feelings? | Escape | 0.496 | 0.829 | 0.615 |
| …had serious conflict with your parents, brother(s) or sister(s) because of your social media use? | Conflict | 0.617 | 0.930 | 0.766 |

*Notes.* CFA = confirmatory factor analysis; SMU = social media use.
[1] Lowest observed factor loading across all 44 countries.
[2] Highest observed factor loading across all 44 countries.
[3] Average factor loading calculated from 44 countries.

CFAs showed that, in all countries, the one-factor model had good model fit (min. CFI and TLI: 0.963 and 0.951, max. RMSEA and SRMR: 0.057 and 0.060). On average, all factor loadings exceeded 0.50 (Table 3.3). In all countries, at least five factor loadings exceeded 0.50. More specifically, for 33 countries, all nine factor loadings exceeded 0.50. In nine countries, there was one item with a factor loading below 0.50. In two countries, there were two items with factor loadings below 0.50. However, the lowest observed factor loading was 0.38 ('persistence' in Greece). Details about the CFA estimated by country can be found in the Appendix (Tables A3.5 and A3.6). Overall, the model fit and factor loadings confirm a solid structural validity in all countries.

## Reliability

Ordinal alpha for the nine items on the pooled sample was 0.90. Alpha ranged between 0.84 (Greece) and 0.95 (Azerbaijan), suggesting good reliability across all countries. Reliability estimates for all countries are provided in the Appendix (Table A3.5).

## Measurement Invariance

Table 3.4 shows that constraining the factor loadings and thresholds to be equal across countries did not substantially deteriorate model fit (ΔCFI = -0.010, ΔRMSEA = 0.003), indicating that the factor structure was comparable across countries. Given that the observed change in CFI was 0.10, which is the maximum value allowed for establishing measurement invariance (F. F. Chen, 2007), a sensitivity analysis was conducted. Specifically, the pooled sample was randomly split in half, after which the measurement invariance analysis was repeated using the two subsamples. For both subsamples, measurement invariance was established (for both subsamples: configural CFI = 0.981, RMSEA = 0.038; scalar CFI = 0.971, RMSEA = 0.041).

**Table 3.4**

*Summary Table Measurement Invariance Analysis (n = 222,532 in 44 Countries)*

| | **Model fit** | | | | | **Change in model fit** | |
|---|---|---|---|---|---|---|---|
| | **Par.** | **CFI** | **TLI** | **RMSEA** | **SRMR** | **ΔCFI** | **ΔRMSEA** |
| **Country invariance** | | | | | | | |
| Configural | 792 | 0.979 | 0.972 | 0.037 | 0.040 | | |
| Scalar | 491 | 0.969 | 0.967 | 0.040 | 0.045 | -0.010 | 0.003 |
| | | | | | | | |
| **Gender invariance** | | | | | | | |
| Configural | 36 | 0.979 | 0.972 | 0.035 | 0.034 | | |
| Scalar | 29 | 0.978 | 0.974 | 0.034 | 0.034 | -0.001 | -0.001 |
| By country, minimum | | | | | | -0.006 | |
| By country, maximum | | | | | | | 0.003 |
| | | | | | | | |
| **Age invariance**[1] | | | | | | | |
| Configural | 54 | 0.975 | 0.967 | 0.035 | 0.034 | | |
| Scalar | 40 | 0.974 | 0.970 | 0.033 | 0.034 | -0.001 | -0.002 |
| By country, minimum | | | | | | -0.013 | |
| By country, maximum | | | | | | | 0.008 |
| | | | | | | | |
| **Socioeconomic invariance**[2] | | | | | | | |
| Configural | 54 | 0.981 | 0.975 | 0.035 | 0.033 | | |
| Scalar | 40 | 0.982 | 0.979 | 0.032 | 0.033 | 0.001 | -0.003 |
| By country, minimum | | | | | | -0.002 | |
| By country, maximum | | | | | | | -0.001 |

*Notes.* Par. = number of free parameters; CFI = comparative fit index; TLI = Tucker Lewis index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual.
[1] *n* = 221,093 due to missing values of age.
[2] *n* = 212,353 due to missing values of socioeconomic status.

The pooled sample showed measurement invariance with respect to gender, age, and socioeconomic status (Table 3.4). By country, gender invariance was established in all countries, whereby the strongest decrease in CFI was observed in Greece and Hungary (ΔCFI = -0.006), and the strongest increase in RMSEA was observed in Greece (ΔRMSEA = 0.003). Age invariance was not established in Malta (ΔCFI = -0.013, ΔRMSEA = 0.008). In the other 43 countries, age invariance was established, whereby the highest decrease in CFI and increase in RMSEA was observed in Romania (ΔCFI = -0.007, ΔRMSEA = 0.004). Socioeconomic invariance was established in all countries because CFI decreased with not more than 0.002 (Sweden) and RMSEA decreased in all countries with at least 0.001 (Kazakhstan). The invariance analyses by country are presented in the Appendix (Tables A3.7-A3.9).

## Criterion Validity

Table 3.5 shows the means in life satisfaction, psychosomatic complaints, and intensity of online communication via social media, by problematic SMU, as well as the effect sizes of the mean differences. Although the outcome measures show skew distributions, it is unlikely that this significantly affects the results, because large samples were used (Schmidt & Finan, 2018). Furthermore, mean differences were estimated using regression with MLR-estimation, which provides estimates robust to non-normality (Kline, 2011).

In the pooled sample, problematic users reported lower levels of life satisfaction, higher levels of psychosomatic complaints, and higher online communication intensity than non-problematic users. The difference in life satisfaction and intensity of online communication between problematic and non-problematic users was small to moderate, whereas the difference in psychosomatic complaints was moderate to large (Table 3.5). The analyses by country showed that there was a negative association between problematic SMU and life satisfaction in 40 countries, with effect sizes ranging from small (Albania: $\beta$ = -0.193, $p$ = 0.021) to moderate/large (England: $\beta$ = -0.682, $p$ < 0.001). In four countries, there were no significant differences in life satisfaction (Azerbaijan, Georgia, Kazakhstan, and Republic of Moldova). The positive association between problematic SMU and psychosomatic complaints was observed in all countries, with effect sizes ranging from small/moderate (Norway: $\beta$ = 0.309, $p$ < 0.001) to large (Azerbaijan: $\beta$ = 0.924, $p$ < 0.001). The positive association between problematic SMU and the intensity of online communication was observed in 41 countries and ranged from small (Armenia: $\beta$ = 0.163, $p$ = 0.023) to moderate/large (Switzerland: $\beta$ = 0.635, $p$ < 0.001). In two countries (Georgia and the Russian Federation), there were no significant differences in the intensity of online communication. In one country, there was a small/moderate negative association between problematic SMU and the intensity of online communication (Azerbaijan: $\beta$ = -0.273, $p$ = 0.001). Estimates by country are presented in the Appendix (Tables A3.10-A3.12).

**Table 3.5**

*Summary Table Life Satisfaction, Psychosomatic Complaints, and Intensity of Online Communication, by Problematic SMU (n = 222,532 in 44 Countries)*

| | **Means** | | | | | **Effect size mean differences** | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Mean** | **95% LL** | **95% UL** | **Observed range mean[1]** | | **$\beta$** | ***SE*** | ***p*** | **Countries[2]** | **Observed range $\beta$[3]** | |
| | **Life satisfaction (*M* = 7.73, *SD* = 2.03, min. = 0, max. = 10)** | | | | | | | | | | |
| Non-problematic | 7.79 | 7.79 | 7.80 | 6.67 | 8.56 | | | | | | |
| Problematic | 6.96 | 6.92 | 7.00 | 6.13 | 8.30 | -0.395 | 0.011 | <0.001 | 40 | -0.682 | -0.193 |
| | **Psychosomatic complaints (*M* = 2.08, *SD* = 0.90, min. = 1, max. = 5)** | | | | | | | | | | |
| Non-problematic | 2.03 | 2.03 | 2.04 | 1.60 | 2.39 | | | | | | |
| Problematic | 2.62 | 2.60 | 2.63 | 2.06 | 3.26 | 0.648 | 0.010 | <0.001 | 44 | 0.309 | 0.924 |
| | **Intensity of online communication (*M* = 3.76, *SD* = 1.29, min. = 1, max. = 5)** | | | | | | | | | | |
| Non-problematic | 3.72 | 3.72 | 3.73 | 2.84 | 4.12 | | | | | | |
| Problematic | 4.15 | 4.13 | 4.17 | 2.33 | 4.45 | 0.313 | 0.009 | <0.001 | 41 | 0.163 | 0.635 |

*Notes.* SMU = social media use; LL = confidence interval lower limit; UL = confidence interval upper limit; $\beta$ = STDY-standardized (i.e., *B*/standard deviation(Y)), controlled for gender, age, and socioeconomic status; *SE* = standard error; *p* = p-value.

[1] Observed means across 44 countries.

[2] Number of countries where a significant association was observed in the same direction as in the pooled sample.

[3] Observed range STDY-standardized $\beta$ across countries where a significant association was observed in the same direction as in the pooled sample, controlled for gender, age, and socioeconomic status.

Overall, for almost all countries, the associations were significant and in the expected directions, which confirms appropriate criterion validity. To investigate the robustness of this conclusion, we repeated the analyses while defining problematic SMU as reporting at least five or seven symptoms, instead of six. Results were highly comparable, suggesting that our findings were not sensitive to our operationalization of problematic SMU. A summary of this analysis is provided in the Appendix (Table A3.13).

# Discussion

The present study is the first to systematically analyze the psychometric properties of a problematic SMU-scale across comparable nationally representative samples of adolescents in many countries. Findings from

222,253 adolescents from 44 countries showed that the SMD-scale has good psychometric properties within a broad international context and demonstrates its suitability for cross-national comparisons in problematic SMU. First, the CFA confirmed good structural validity of the scale across all countries. Second, the internal consistency of the items was good in all countries, suggesting that the scale provides reliable scores. Third, the factor structure of the scale was measurement invariant across countries. Also, gender and socioeconomic status invariance was established in all countries, and age invariance in all countries except Malta. Fourth, in line with previous research, in almost all countries, problematic SMU was negatively associated with mental wellbeing and positively with the intensity of online communication, confirming good criterion validity.

All countries showed good structural validity by means of good model fit of a one-factor model and high factor loadings of the items. These findings suggest that all nine items substantially contribute to the underlying construct of problematic SMU. This implies that alongside the six items referring to the core criteria of addiction (Griffiths, 2005; Griffiths et al., 2014), the three additional items that distinguish the SMD-scale from other problematic SMU-scales (Andreassen et al., 2012, 2016), including problems, displacement, and deception, further contribute to the conceptualization of problematic SMU. Hence, with their inclusion, the SMD-scale may advance the measurement of problematic SMU. To verify this suggestion, future studies comparing the psychometric properties of the SMD-scale with scales based on only the six core criteria of addiction are recommended.

The finding that the factor model was measurement invariant across countries implies that adolescents from different countries interpret the questions from the scale in a similar manner and that the scale measures the same underlying construct across countries (Davidov, 2010). Hence, the scale is suited for measuring and comparing adolescents' level of problematic SMU in international surveys. Furthermore, as a next step, future research examining the potential reasons for country-level differences in the prevalence of problematic SMU are considered promising. Moreover, the finding that gender, age, and socioeconomic invariance was observed in all countries (except for age invariance in one country), implies that the scale also measures the same underlying construct for boys, girls, 11-, 13-, 15-year-olds, and adolescents with low, middle, and high socioeconomic status. Therefore, researchers can use the scale to accurately identify which of these subgroups are at risk of problematic SMU, which is considered important given the possible detrimental consequences of problematic SMU (Boer, Stevens, et al., 2020; Boer, Stevens, Finkenauer, De Looze, et al., 2021).

The observed pooled effect sizes from the criterion validity analysis were in line with the literature (Frost & Rickwood, 2017; Huang, 2020; Marino et al., 2018b; Parry et al., 2020). Problematic SMU was more strongly associated with psychosomatic complaints than with low life satisfaction, which parallels review studies showing a stronger relationship between problematic SMU and indicators of negative mental wellbeing (e.g., depression) compared with indicators of positive mental wellbeing (e.g., self-esteem) (Huang, 2020; Marino et al., 2018b). Not only do these findings confirm that the scores on the scale are related to constructs they should theoretically be related to; they also highlight that, worldwide, problematic users face several similar mental health risks. If these associations occur because problematic SMU leads to significant psychological harm, as suggested by some longitudinal studies (Boer, Stevens, Finkenauer, De Looze, et al., 2021; Raudsepp, 2019), then problematic SMU may reflect addiction-like behavior, which has been questioned (Kardefelt-Winther et al., 2017). However, to verify this, more research is required, particularly focusing on whether problematic SMU impairs mental health and other aspects of daily life, assessed in clinical settings. Furthermore, the finding that problematic SMU is a global risk factor for adolescents' mental wellbeing emphasizes the relevance for the development of prevention and intervention programs on (reducing) problematic SMU, for example by supporting adolescents in regulating their SMU.

In addition, the observed small to moderate effect size of the (positive) association between problematic SMU and online communication intensity may be regarded as counterintuitive (Frost & Rickwood, 2017). However, this effect size is in line with earlier meta-analytic findings on the relationship between problematic SMU and the intensity of (tracked) SMU activities (Frost & Rickwood, 2017; Parry et al., 2020), which supports the suggestion that the intensity of SMU activities and problematic SMU should be regarded as related but different dimensions of SMU (Boer, Stevens, Finkenauer, De Looze, et al., 2021; Boer, Van den Eijnden, et al., 2020; Parry et al., 2020). Although many problematic users may engage in a high intensity of online communication, there may also problematic users who do not show intensive online communication. These latter users may experience a mismatch between their desired and actual online social network: they could be preoccupied with social media without having the desired network to interact with. Conversely, adolescents engaging in intensive online communication may be well able to regulate their online activities without experiencing problematic SMU.

## Strengths and Limitations

The present study has several strengths, related to the data that includes many nationally representative subsamples. However, there are also some limitations that should be acknowledged. First, the cross-sectional design of the study precludes the possibility to investigate the predictive validity and the test-retest reliability of the scale. Second, the present study included mainly European adolescents. Third, other elements of validity, including convergent and discriminant validity, were not assessed. Considering these three limitations, more validation research on the SMD-scale using longitudinal data and data from non-European adolescents, and including more validation analyses, is warranted to extend current knowledge on the psychometric properties of the scale. Fourth, scores on the SMD-scale are based on self-reports, which may deviate from assessments by others. As such, the reported prevalence rates of problematic SMU may be under- or overestimated. Research comparing self-report scores with scores from, for example, teachers or parents, is considered important. Fifth, the evaluation criteria for measurement invariance testing were obtained from WLSMV-estimation, which may not perform as well as with MLR-estimation (Sass et al., 2014). However, with categorical items, measurement invariance analysis with MLR-estimation can only be conducted using Chi-square-difference tests, which may falsely reject measurement invariance due to its sensitivity to large sample sizes (F. F. Chen, 2007; Cheung & Rensvold, 2002). Sixth, the present study defined adolescents reporting six or more symptoms as problematic users. Although this definition was based on findings from latent class analyses (Boer, Stevens, Finkenauer, Koning, et al., 2021), research using clinical data is required to verify whether this definition adequately identifies problematic users, for example by comparing assessments of problematic SMU by a clinician with assessments using our used definition based on the SMD-scale. Seventh, although response rates were generally high, results are possibly somewhat affected by voluntary response bias given the sampling design.

## Conclusion

Given the widespread adoption of social media among adolescents and the risks that are associated with addiction-like problematic SMU observed worldwide, it is essential that a suitable measure is available to allow for adequate assessments and cross-national comparisons of problematic SMU. Findings from the present study demonstrate that the SMD-scale is reliable, valid, and comparable across many national contexts, thereby facilitating future research on problematic SMU.

# Appendix

**Table A3.1**

*The Social Media Disorder-Scale*

**We are interested in your experiences with social media. The term social media refers to social network sites (e.g., Facebook, [add other local examples]) and instant messengers (e.g., [insert local examples], WhatsApp, Snapchat, Facebook messenger).**

***During the past year, have you... Please tick one circle for each line.***

| | **No** | **Yes** |
|---|---|---|
| ...regularly found that you can't think of anything else but the moment that you will be able to use social media again? | O | O |
| ...regularly felt dissatisfied because you wanted to spend more time on social media? | O | O |
| ...often felt bad when you could not use social media? | O | O |
| ...tried to spend less time on social media, but failed? | O | O |
| ...regularly neglected other activities (e.g., hobbies, sport) because you wanted to use social media? | O | O |
| ...regularly had arguments with others because of your social media use? | O | O |
| ...regularly lied to your parents or friends about the amount of time you spend on social media? | O | O |
| ...often used social media to escape from negative feelings? | O | O |
| ...had serious conflict with your parents, brother(s) or sister(s) because of your social media use? | O | O |

**Scoring instructions for assessor:**
From top to bottom, the nine items represent the following criteria: preoccupation, tolerance, withdrawal, persistence, displacement, problem, deception, escape, and conflict (Van den Eijnden et al., 2016). Respondents with six to nine *yes*-responses may be coded as 'problematic user', and respondents with zero to five *yes*-responses as 'non-problematic user' (Boer, Stevens, Finkenauer, Koning, et al., 2021).

**Table A3.2**

*Prevalence Rates Problematic SMU Items, by Country (n = 222,532 in 44 Countries)*

| | | Problematic SMU Items | | | | | | | | | Probl. |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | *n* | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | SMU[1] |
| Albania | 1650 | 23.43% | 22.19% | 35.53% | **41.13%** | 23.84% | 39.64% | *16.96%* | 31.82% | 19.85% | 11.71% |
| Armenia | 4430 | 16.28% | 14.19% | 21.45% | **23.58%** | 14.38% | 16.39% | *11.49%* | 20.80% | 13.88% | 6.08% |
| Austria | 4011 | 20.14% | 15.93% | 18.32% | 28.54% | 17.68% | *11.87%* | 12.98% | **29.18%** | 14.94% | 4.85% |
| Azerbaijan | 3778 | 25.73% | 21.56% | 20.12% | **24.89%** | 18.31% | 18.06% | *15.68%* | 22.72% | 17.09% | 9.99% |
| Belgium (Flanders) | 4117 | 28.04% | 16.79% | 18.63% | **30.78%** | 15.36% | 18.97% | 16.12% | 29.05% | *13.40%* | 6.73% |
| Belgium (Wallonia) | 5221 | 23.60% | 24.98% | 24.46% | 29.95% | *14.84%* | 23.36% | 18.13% | **32.43%** | 18.03% | 8.62% |
| Canada | 12355 | 18.30% | 15.46% | 17.18% | 27.70% | 12.51% | 15.41% | 13.77% | **31.34%** | *10.29%* | 6.28% |
| Croatia | 4913 | 26.22% | 19.94% | 24.49% | **38.54%** | 19.18% | 20.99% | 16.57% | 30.86% | *14.99%* | 10.31% |
| Czechia | 11162 | 16.40% | 14.40% | 18.44% | 26.51% | 13.57% | 15.21% | *10.82%* | **27.29%** | 12.48% | 5.26% |
| Denmark | 3113 | 25.36% | 8.13% | 13.83% | 26.82% | *7.03%* | 13.48% | 9.39% | **31.41%** | 7.92% | 3.91% |
| England | 3306 | 19.88% | 18.31% | 23.57% | 31.35% | 13.75% | 18.58% | 13.77% | **34.22%** | *11.56%* | 7.77% |
| Estonia | 4622 | 19.13% | 19.07% | 21.39% | 29.45% | 11.08% | 14.50% | *10.83%* | **35.18%** | 12.26% | 5.81% |
| Finland | 3067 | 34.73% | 18.34% | 19.38% | **31.41%** | 18.78% | 17.46% | *12.94%* | 30.87% | 14.44% | 10.02% |
| France | 8621 | 22.66% | 22.86% | 22.00% | **26.35%** | *11.42%* | 19.37% | 17.10% | 26.32% | 13.22% | 7.41% |
| Georgia | 4067 | 18.65% | 19.91% | 21.76% | **31.83%** | 18.76% | 13.89% | *9.46%* | 11.42% | 10.10% | 4.33% |
| Germany | 4126 | 17.61% | 17.51% | 19.60% | **29.92%** | 14.98% | 14.05% | *13.06%* | 26.05% | 18.74% | 5.28% |
| Greece | 3715 | 23.67% | 23.28% | 30.78% | 32.09% | *15.14%* | 24.15% | 18.69% | **42.13%** | 22.01% | 9.98% |
| Hungary | 3715 | 16.66% | 21.22% | 19.81% | 27.80% | 15.46% | 24.55% | *9.27%* | **30.76%** | 13.54% | 5.38% |
| Iceland | 6693 | 14.97% | 12.59% | 11.63% | **28.70%** | *7.11%* | 13.64% | 12.25% | 18.60% | 7.94% | 4.66% |
| Ireland | 3628 | 28.42% | 23.21% | 31.04% | 37.43% | *14.77%* | 28.20% | 23.26% | **40.62%** | 14.80% | 12.01% |
| Israel | 7134 | 24.12% | 17.19% | 14.40% | **23.08%** | 17.03% | 15.14% | 8.76% | 19.24% | *8.02%* | 5.02% |
| Italy | 4069 | 28.80% | *16.93%* | 22.68% | 37.09% | 22.56% | 28.71% | 25.88% | **38.84%** | 24.52% | 10.86% |
| Kazakhstan | 4488 | 17.09% | 13.07% | 13.75% | **22.46%** | 15.95% | 12.05% | *9.54%* | 19.65% | 9.76% | 4.38% |
| Latvia | 4143 | 17.08% | 15.04% | 22.22% | **36.08%** | 14.13% | 13.65% | *11.49%* | 34.89% | 12.95% | 5.31% |
| Lithuania | 3685 | 21.15% | 18.28% | 19.52% | 30.14% | 15.47% | 15.92% | *12.53%* | **31.65%** | 16.98% | 7.78% |
| Luxembourg | 3889 | 22.57% | 20.82% | 25.55% | **33.48%** | *16.60%* | 17.35% | 16.62% | 31.96% | 19.90% | 7.56% |
| Malta | 2504 | 32.04% | 35.34% | **48.21%** | 42.10% | *21.18%* | 33.40% | 22.31% | 35.39% | 32.23% | 16.41% |
| Netherlands | 4579 | 26.10% | 7.33% | 15.70% | 24.52% | 13.14% | 14.26% | 10.99% | **28.41%** | *4.67%* | 3.20% |
| North Macedonia | 4575 | 31.16% | 25.63% | 32.48% | 36.41% | 26.13% | 17.21% | *12.17%* | **47.02%** | 14.97% | 9.55% |
| Norway | 3053 | 21.57% | 17.65% | 21.97% | 29.34% | 16.06% | 19.24% | 17.27% | **30.27%** | *12.91%* | 9.19% |
| Poland | 5055 | 22.83% | 20.68% | 26.31% | 24.87% | 17.18% | 20.83% | 16.32% | **32.85%** | *14.77%* | 7.62% |
| Portugal | 5866 | 19.40% | 17.59% | 20.58% | 25.44% | *9.42%* | 14.99% | 9.53% | **27.25%** | 10.96% | 5.86% |
| Republic of Moldova | 4429 | 23.86% | 24.34% | 24.14% | 34.18% | 22.28% | 19.87% | *15.72%* | **40.95%** | 18.37% | 7.95% |
| Romania | 4483 | 27.99% | 28.29% | 27.74% | 37.66% | 25.76% | 28.65% | 25.58% | **45.41%** | *18.90%* | 13.04% |
| Russian Federation | 4061 | 19.98% | 16.49% | 16.23% | 25.56% | 18.53% | 15.44% | *11.76%* | **28.62%** | 18.03% | 7.65% |
| Scotland | 4916 | 23.42% | 19.46% | 25.65% | **35.03%** | 15.25% | 23.08% | 15.16% | 34.18% | *11.61%* | 9.36% |
| Serbia | 3740 | 18.10% | 17.09% | 15.82% | **31.52%** | 16.52% | 15.84% | 13.79% | 31.43% | *12.65%* | 6.96% |
| Slovenia | 5126 | 14.16% | *11.74%* | 15.47% | **30.96%** | 12.93% | 13.50% | 13.00% | 21.96% | 13.24% | 5.24% |
| Spain | 4070 | 27.86% | 29.63% | 28.39% | **35.66%** | 24.38% | 33.77% | 26.75% | 33.45% | *22.68%* | 14.27% |
| Sweden | 4006 | 20.15% | 15.43% | 14.99% | 31.53% | *8.55%* | 14.61% | 12.60% | **35.44%** | 10.18% | 5.17% |
| Switzerland | 7122 | 17.10% | 16.53% | 15.63% | **30.36%** | *12.40%* | 16.66% | 12.86% | 27.53% | 16.33% | 4.48% |
| Turkey | 5541 | 25.14% | 30.23% | 25.17% | 33.35% | *17.01%* | 23.92% | 19.02% | **35.39%** | 24.11% | 10.70% |
| Ukraine | 6232 | 23.69% | 18.79% | 15.01% | **36.67%** | 17.38% | 16.69% | *10.53%* | 36.13% | 13.38% | 6.79% |
| Wales | 15456 | 25.88% | 21.16% | 26.45% | 35.82% | 18.33% | 24.94% | 17.58% | **35.93%** | *15.12%* | 12.27% |

*Notes.* SMU = social media use; (1) = preoccupation; (2) = tolerance; (3) = withdrawal; (4) = persistence; (5) = displacement; (6) = problem; (7) = deception; (8) = escape; (9) = conflict. Rates in italics indicate the row minimum with respect to the nine items; rates in boldface indicate the row maximum with respect to the nine items.

[1] Problematic SMU, i.e., presence of six to nine symptoms. The present prevalence estimates for problematic SMU slightly differ from previously reported prevalence estimates using the same data (Boer, Van den Eijnden, et al., 2020) (*M*Δ = -0.01 percentage point, min. = -0.29 in Italy, max. = +0.42 in Canada). These small differences are the result of improved estimation of missing data due to inclusion of more data (countries) in the present study. Also, the present prevalence estimate of the Belgian (Wallonia) sample deviates more from the previous report (Boer, Van den Eijnden, et al., 2020) (+0.6 percentage point), because the present study used a larger subsample that became available in a later release of the data.

**Table A3.3**

*EFA Eigenvalues and Parallel Test Results, Calibration Samples, by Country (n = 111,254 in 44 Countries)*

| Country | *n* | Empirical eigenvalues[1] | | | | | | | | | 95th percentile of random eigenvalues[2] | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
| Albania | 825 | **4.41** | 0.86 | 0.80 | 0.67 | 0.64 | 0.49 | 0.44 | 0.37 | 0.33 | *1.21* | 1.14 | 1.10 | 1.06 | 1.02 | 0.99 | 0.96 | 0.92 | 0.88 |
| Armenia | 2215 | **5.07** | 0.76 | 0.67 | 0.64 | 0.46 | 0.43 | 0.39 | 0.33 | 0.25 | *1.13* | 1.09 | 1.06 | 1.04 | 1.01 | 0.99 | 0.97 | 0.95 | 0.93 |
| Austria | 2005 | **4.14** | 0.86 | 0.77 | 0.69 | 0.62 | 0.56 | 0.52 | 0.44 | 0.40 | *1.13* | 1.09 | 1.06 | 1.04 | 1.01 | 0.99 | 0.97 | 0.95 | 0.93 |
| Azerbaijan | 1889 | **6.50** | 0.67 | 0.39 | 0.36 | 0.34 | 0.24 | 0.20 | 0.17 | 0.13 | *1.14* | 1.09 | 1.06 | 1.04 | 1.02 | 0.99 | 0.97 | 0.95 | 0.92 |
| Belgium (Flanders) | 2058 | **4.62** | 0.85 | 0.75 | 0.60 | 0.55 | 0.49 | 0.43 | 0.37 | 0.34 | *1.13* | 1.09 | 1.06 | 1.04 | 1.01 | 0.99 | 0.97 | 0.95 | 0.93 |
| Belgium (Wallonia) | 2610 | **4.43** | 0.87 | 0.73 | 0.67 | 0.65 | 0.48 | 0.43 | 0.40 | 0.33 | *1.12* | 1.08 | 1.06 | 1.03 | 1.01 | 1.00 | 0.98 | 0.96 | 0.93 |
| Canada | 6177 | **4.99** | 0.87 | 0.74 | 0.56 | 0.52 | 0.43 | 0.36 | 0.28 | 0.26 | *1.07* | 1.05 | 1.04 | 1.02 | 1.01 | 1.00 | 0.98 | 0.97 | 0.96 |
| Croatia | 2456 | **5.10** | 0.83 | 0.69 | 0.53 | 0.52 | 0.39 | 0.36 | 0.32 | 0.28 | *1.12* | 1.08 | 1.06 | 1.03 | 1.01 | 0.99 | 0.98 | 0.95 | 0.93 |
| Czechia | 5581 | **4.94** | 0.78 | 0.73 | 0.61 | 0.54 | 0.41 | 0.38 | 0.33 | 0.29 | *1.08* | 1.06 | 1.04 | 1.02 | 1.01 | 1.00 | 0.98 | 0.97 | 0.96 |
| Denmark | 1556 | **4.89** | 0.88 | 0.79 | 0.66 | 0.57 | 0.42 | 0.33 | 0.25 | 0.22 | *1.15* | 1.10 | 1.07 | 1.04 | 1.02 | 0.99 | 0.97 | 0.94 | 0.91 |
| England | 1653 | **5.31** | 0.75 | 0.66 | 0.55 | 0.53 | 0.36 | 0.34 | 0.27 | 0.23 | *1.15* | 1.10 | 1.07 | 1.04 | 1.02 | 0.99 | 0.97 | 0.95 | 0.92 |
| Estonia | 2311 | **4.66** | 0.86 | 0.76 | 0.65 | 0.60 | 0.47 | 0.42 | 0.33 | 0.25 | *1.13* | 1.08 | 1.06 | 1.03 | 1.01 | 0.99 | 0.97 | 0.95 | 0.93 |
| Finland | 1533 | **5.91** | 0.69 | 0.53 | 0.47 | 0.38 | 0.37 | 0.26 | 0.21 | 0.19 | *1.16* | 1.11 | 1.07 | 1.04 | 1.02 | 0.99 | 0.97 | 0.94 | 0.91 |
| France | 4310 | **4.80** | 0.79 | 0.69 | 0.62 | 0.56 | 0.53 | 0.39 | 0.35 | 0.28 | *1.09* | 1.06 | 1.04 | 1.03 | 1.01 | 1.00 | 0.98 | 0.97 | 0.95 |
| Georgia | 2033 | **4.76** | 0.86 | 0.71 | 0.68 | 0.51 | 0.43 | 0.42 | 0.38 | 0.25 | *1.13* | 1.09 | 1.06 | 1.04 | 1.01 | 0.99 | 0.97 | 0.95 | 0.92 |
| Germany | 2063 | **4.51** | 0.85 | 0.73 | 0.66 | 0.64 | 0.47 | 0.44 | 0.37 | 0.34 | *1.13* | 1.09 | 1.06 | 1.04 | 1.01 | 0.99 | 0.97 | 0.95 | 0.92 |
| Greece | 1857 | **4.19** | 0.85 | 0.81 | 0.67 | 0.62 | 0.57 | 0.48 | 0.44 | 0.37 | *1.14* | 1.09 | 1.06 | 1.04 | 1.01 | 0.99 | 0.97 | 0.95 | 0.92 |
| Hungary | 1857 | **4.11** | 0.92 | 0.89 | 0.71 | 0.68 | 0.51 | 0.45 | 0.38 | 0.36 | *1.14* | 1.09 | 1.06 | 1.04 | 1.01 | 0.99 | 0.97 | 0.95 | 0.92 |
| Iceland | 3346 | **5.86** | 0.69 | 0.58 | 0.44 | 0.39 | 0.35 | 0.28 | 0.22 | 0.19 | *1.10* | 1.07 | 1.05 | 1.03 | 1.01 | 0.99 | 0.98 | 0.96 | 0.94 |
| Ireland | 1814 | **4.75** | 0.95 | 0.72 | 0.64 | 0.56 | 0.44 | 0.38 | 0.29 | 0.27 | *1.14* | 1.10 | 1.07 | 1.04 | 1.02 | 0.99 | 0.97 | 0.95 | 0.92 |
| Israel | 3567 | **4.61** | 0.98 | 0.65 | 0.62 | 0.56 | 0.48 | 0.43 | 0.39 | 0.29 | *1.10* | 1.07 | 1.05 | 1.03 | 1.01 | 1.00 | 0.98 | 0.96 | 0.94 |
| Italy | 2034 | **4.13** | 0.85 | 0.83 | 0.67 | 0.67 | 0.52 | 0.49 | 0.47 | 0.38 | *1.13* | 1.09 | 1.06 | 1.04 | 1.01 | 0.99 | 0.97 | 0.95 | 0.93 |
| Kazakhstan | 2244 | **5.17** | 0.75 | 0.66 | 0.54 | 0.46 | 0.45 | 0.37 | 0.34 | 0.27 | *1.13* | 1.09 | 1.06 | 1.03 | 1.01 | 0.99 | 0.97 | 0.95 | 0.93 |
| Latvia | 2071 | **4.47** | 0.90 | 0.77 | 0.70 | 0.60 | 0.49 | 0.42 | 0.38 | 0.28 | *1.13* | 1.09 | 1.06 | 1.04 | 1.02 | 0.99 | 0.97 | 0.95 | 0.93 |
| Lithuania | 1842 | **5.17** | 0.80 | 0.71 | 0.60 | 0.45 | 0.42 | 0.33 | 0.30 | 0.24 | *1.14* | 1.10 | 1.06 | 1.04 | 1.01 | 0.99 | 0.97 | 0.95 | 0.92 |
| Luxembourg | 1944 | **4.10** | 0.87 | 0.78 | 0.76 | 0.68 | 0.53 | 0.51 | 0.42 | 0.37 | *1.14* | 1.09 | 1.06 | 1.04 | 1.02 | 0.99 | 0.97 | 0.95 | 0.92 |
| Malta | 2287 | **4.32** | 0.87 | 0.84 | 0.70 | 0.66 | 0.53 | 0.42 | 0.34 | 0.32 | *1.13* | 1.09 | 1.06 | 1.03 | 1.01 | 0.99 | 0.97 | 0.95 | 0.93 |
| Netherlands | 1252 | **4.32** | 0.76 | 0.75 | 0.71 | 0.65 | 0.54 | 0.49 | 0.42 | 0.35 | *1.17* | 1.12 | 1.08 | 1.05 | 1.02 | 0.99 | 0.96 | 0.93 | 0.91 |
| North Macedonia | 2289 | **4.36** | 0.79 | 0.76 | 0.69 | 0.64 | 0.61 | 0.44 | 0.40 | 0.31 | *1.13* | 1.09 | 1.06 | 1.03 | 1.01 | 0.99 | 0.98 | 0.95 | 0.93 |
| Norway | 1526 | **5.73** | 0.72 | 0.59 | 0.54 | 0.39 | 0.33 | 0.31 | 0.25 | 0.14 | *1.15* | 1.11 | 1.07 | 1.04 | 1.02 | 0.99 | 0.97 | 0.94 | 0.91 |
| Poland | 2527 | **4.48** | 0.86 | 0.76 | 0.66 | 0.56 | 0.50 | 0.44 | 0.39 | 0.35 | *1.12* | 1.08 | 1.05 | 1.03 | 1.01 | 0.99 | 0.98 | 0.96 | 0.93 |
| Portugal | 2933 | **5.35** | 0.85 | 0.60 | 0.49 | 0.45 | 0.36 | 0.33 | 0.31 | 0.27 | *1.11* | 1.08 | 1.05 | 1.03 | 1.01 | 0.99 | 0.98 | 0.96 | 0.94 |
| Republic of Moldova | 2214 | **3.80** | 0.88 | 0.80 | 0.70 | 0.69 | 0.62 | 0.61 | 0.51 | 0.38 | *1.13* | 1.09 | 1.06 | 1.03 | 1.01 | 0.99 | 0.97 | 0.95 | 0.93 |

*Notes.* EFA = exploratory factor analysis; the EFA and parallel analysis were conducted using the Mplus default settings for EFA with categorical indicators (using Oblique Geomin rotation); Boldface numbers denote eigenvalues higher than one; Italics numbers denote 95 percentile values that exceeded the respective empirical eigenvalues.

[1] Derived from the tetrachoric correlation matrix as appropriate for categorical items.

[2] Results from 1000 randomly generated eigenvalues.

3

**Table A3.3 (Continued)**

*EFA Eigenvalues and Parallel Test Results, Calibration Samples, by Country (n = 111,254 in 44 Countries)*

| Country | *n* | Empirical eigenvalues[1] | | | | | | | | | 95th percentile of random eigenvalues[2] | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
| Romania | 2241 | **4.06** | 0.88 | 0.83 | 0.70 | 0.66 | 0.59 | 0.49 | 0.44 | 0.37 | *1.13* | 1.09 | 1.06 | 1.03 | 1.01 | 0.99 | 0.97 | 0.95 | 0.93 |
| Russian Federation | 2030 | **5.57** | 0.66 | 0.60 | 0.48 | 0.43 | 0.39 | 0.37 | 0.26 | 0.23 | *1.13* | 1.09 | 1.06 | 1.04 | 1.01 | 0.99 | 0.97 | 0.95 | 0.92 |
| Scotland | 2458 | **5.04** | 0.88 | 0.66 | 0.58 | 0.52 | 0.43 | 0.39 | 0.30 | 0.20 | *1.12* | 1.08 | 1.06 | 1.03 | 1.01 | 0.99 | 0.98 | 0.96 | 0.93 |
| Serbia | 1870 | **5.09** | 0.88 | 0.76 | 0.62 | 0.47 | 0.38 | 0.34 | 0.30 | 0.17 | *1.14* | 1.10 | 1.06 | 1.04 | 1.01 | 0.99 | 0.97 | 0.95 | 0.92 |
| Slovenia | 2563 | **5.23** | 0.83 | 0.61 | 0.53 | 0.46 | 0.39 | 0.36 | 0.32 | 0.28 | *1.12* | 1.08 | 1.05 | 1.03 | 1.01 | 0.99 | 0.98 | 0.96 | 0.93 |
| Spain | 2035 | **5.32** | 0.75 | 0.60 | 0.57 | 0.48 | 0.39 | 0.36 | 0.31 | 0.21 | *1.13* | 1.09 | 1.06 | 1.04 | 1.01 | 0.99 | 0.97 | 0.95 | 0.93 |
| Sweden | 2003 | **4.61** | **1.03** | 0.69 | 0.66 | 0.57 | 0.43 | 0.40 | 0.36 | 0.26 | *1.13* | 1.09 | 1.06 | 1.04 | 1.01 | 0.99 | 0.97 | 0.95 | 0.92 |
| Switzerland | 3561 | **4.06** | 0.83 | 0.75 | 0.72 | 0.66 | 0.59 | 0.52 | 0.45 | 0.42 | *1.10* | 1.07 | 1.05 | 1.03 | 1.01 | 0.99 | 0.98 | 0.96 | 0.94 |
| Turkey | 2770 | **4.63** | 0.82 | 0.69 | 0.58 | 0.53 | 0.51 | 0.46 | 0.43 | 0.34 | *1.11* | 1.08 | 1.05 | 1.03 | 1.01 | 0.99 | 0.98 | 0.96 | 0.94 |
| Ukraine | 3116 | **4.70** | **1.01** | 0.68 | 0.65 | 0.50 | 0.46 | 0.38 | 0.36 | 0.27 | *1.11* | 1.07 | 1.05 | 1.03 | 1.01 | 1.00 | 0.98 | 0.96 | 0.94 |
| Wales | 7728 | **5.49** | 0.71 | 0.63 | 0.53 | 0.43 | 0.39 | 0.32 | 0.29 | 0.23 | *1.07* | 1.05 | 1.03 | 1.02 | 1.01 | 1.00 | 0.99 | 0.98 | 0.96 |

*Notes.* EFA = exploratory factor analysis; the EFA and parallel analysis were conducted using the Mplus default settings for EFA with categorical indicators (using Oblique Geomin rotation); Boldface numbers denote eigenvalues higher than one; Italics numbers denote 95 percentile values that exceeded the respective empirical eigenvalues.

[1] Derived from the tetrachoric correlation matrix as appropriate for categorical items.

[2] Results from 1000 randomly generated eigenvalues.

**Table A3.4**

*EFA Factor Solutions, Calibration Samples, by Country (n = 111,254 in 44 Countries)*

| Country | Model | *n* | Model fit Par. | CFI | TLI | RMSEA | SRMR | Factor loadings Factor | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Albania | m1 | 825 | 18 | 0.986 | 0.982 | 0.031 | 0.043 | 1 | **0.617** | **0.761** | **0.744** | **0.584** | **0.632** | **0.488** | **0.703** | **0.660** | **0.696** |
| | m2 | 825 | 26 | - | - | - | - | - | | | | | | | | | |
| | m3 | 825 | 33 | - | - | - | - | - | | | | | | | | | |
| Armenia | m1 | 2215 | 18 | 0.985 | 0.980 | 0.034 | 0.041 | 1 | **0.719** | **0.737** | **0.739** | **0.582** | **0.759** | **0.714** | **0.812** | **0.612** | **0.761** |
| | m2 | 2215 | 26 | - | - | - | - | - | | | | | | | | | |
| | m3 | 2215 | 33 | - | - | - | - | - | | | | | | | | | |
| Austria | m1 | 2005 | 18 | 0.987 | 0.982 | 0.025 | 0.036 | 1 | **0.681** | **0.646** | **0.702** | **0.567** | **0.533** | **0.644** | **0.661** | **0.517** | **0.680** |
| | m2 | 2005 | 26 | - | - | - | - | - | | | | | | | | | |
| | m3 | 2005 | 33 | 1.000 | 1.002 | 0.000 | 0.015 | 1 | **0.563** | **0.746** | **0.897** | 0.003 | **0.273** | **0.321** | **0.348** | 0.306 | 0.000 |
| | | | | | | | | 2 | 0.064 | -0.011 | -0.223 | **0.611** | 0.033 | -0.004 | 0.012 | **0.360** | -0.026 |
| | | | | | | | | 3 | 0.111 | -0.070 | 0.003 | 0.251 | **0.286** | **0.388** | **0.365** | -0.003 | **0.855** |
| Azerbaijan | m1 | 1889 | 18 | 0.980 | 0.973 | 0.044 | 0.043 | 1 | **0.724** | **0.811** | **0.845** | **0.825** | **0.858** | **0.882** | **0.865** | **0.848** | **0.897** |
| | m2 | 1889 | 26 | - | - | - | - | - | | | | | | | | | |
| | m3 | 1889 | 33 | - | - | - | - | - | | | | | | | | | |
| Belgium (Flanders) | m1 | 2058 | 18 | 0.984 | 0.979 | 0.033 | 0.038 | 1 | **0.688** | **0.739** | **0.762** | **0.477** | **0.594** | **0.694** | **0.695** | **0.631** | **0.731** |
| | m2 | 2058 | 26 | 0.998 | 0.997 | 0.012 | 0.019 | 1 | **0.706** | **0.863** | **0.757** | **0.398** | **0.589** | 0.089 | -0.006 | **0.242** | -0.003 |
| | | | | | | | | 2 | 0.011 | -0.094 | 0.036 | 0.100 | 0.027 | **0.658** | **0.757** | **0.425** | **0.790** |
| | m3 | 2058 | 33 | 1.000 | 1.000 | 0.004 | 0.014 | 1 | **0.667** | **0.822** | **0.771** | 0.270 | **0.586** | 0.029 | 0.007 | -0.003 | -0.028 |
| | m3 | | | | | | | 2 | 0.010 | -0.065 | 0.050 | -0.003 | 0.038 | **0.529** | **0.618** | 0.253 | **0.887** |
| | m3 | | | | | | | 3 | 0.060 | 0.018 | -0.024 | 0.308 | -0.003 | 0.270 | 0.184 | **0.585** | -0.010 |
| Belgium (Wallonia) | m1 | 2610 | 18 | 0.981 | 0.975 | 0.038 | 0.039 | 1 | **0.737** | **0.709** | **0.735** | **0.460** | **0.600** | **0.664** | **0.701** | **0.569** | **0.748** |
| | m2 | 2610 | 26 | - | - | - | - | - | | | | | | | | | |
| | m3 | 2610 | 33 | - | - | - | - | - | | | | | | | | | |
| Canada | m1 | 6177 | 18 | 0.970 | 0.960 | 0.032 | 0.052 | 1 | **0.739** | **0.793** | **0.747** | **0.575** | **0.659** | **0.733** | **0.727** | **0.603** | **0.779** |
| | m2 | 6177 | 26 | 0.994 | 0.989 | 0.017 | 0.025 | 1 | **0.636** | **0.921** | **0.614** | 0.114 | **0.217** | 0.034 | -0.044 | 0.083 | -0.007 |
| | | | | | | | | 2 | **0.177** | -0.007 | **0.212** | **0.501** | **0.495** | **0.739** | **0.812** | **0.560** | **0.830** |
| | m3 | 6177 | 33 | - | - | - | - | - | | | | | | | | | |
| Croatia | m1 | 2456 | 18 | 0.977 | 0.970 | 0.049 | 0.046 | 1 | **0.723** | **0.770** | **0.753** | **0.559** | **0.713** | **0.760** | **0.746** | **0.690** | **0.763** |
| | m2 | 2456 | 26 | 0.996 | 0.993 | 0.023 | 0.022 | 1 | **0.754** | **0.865** | **0.795** | 0.140 | **0.245** | 0.126 | -0.003 | **0.177** | -0.052 |
| | | | | | | | | 2 | 0.022 | -0.036 | 0.014 | **0.454** | **0.512** | **0.679** | **0.781** | **0.553** | **0.861** |
| | m3 | 2456 | 33 | - | - | - | - | - | | | | | | | | | |

*Notes.* EFA = exploratory factor analysis; the EFA was conducted using the Mplus default settings for EFA with categorical indicators (using Oblique Geomin rotation, Weighted Least Square Means and Variance adjusted estimation, with a probit regression link); Par. = number of free parameters; CFI = comparative fit index; TLI = Tucker Lewis index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual; (1) = preoccupation; (2) = tolerance; (3) = withdrawal; (4) = persistence; (5) = displacement; (6) = problem; (7) = deception; (8) = escape; (9) = conflict; Models without results ('-') showed estimation problems. Boldface factor loadings denote significant factor loadings at $p < 0.05$; Dark gray cells denote factor loadings > 0.50.

**Table A3.4 (Continued)**

*EFA Factor Solutions, Calibration Samples, by Country (n = 111,254 in 44 Countries)*

| | | | Model fit | | | | | Factor loadings | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Country** | **Model** | ***n*** | **Par.** | **CFI** | **TLI** | **RMSEA** | **SRMR** | **Factor** | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** | **(7)** | **(8)** | **(9)** |
| Czechia | m1 | 5581 | 18 | 0.978 | 0.971 | 0.037 | 0.042 | 1 | **0.752** | **0.799** | **0.745** | **0.573** | **0.687** | **0.664** | **0.736** | **0.645** | **0.724** |
| | m2 | 5581 | 26 | - | - | - | - | - | | | | | | | | | |
| | m3 | 5581 | 33 | - | - | - | - | - | | | | | | | | | |
| Denmark | m1 | 1556 | 18 | 0.973 | 0.964 | 0.042 | 0.053 | 1 | **0.669** | **0.803** | **0.775** | **0.514** | **0.694** | **0.718** | **0.763** | **0.548** | **0.859** |
| | m2 | 1556 | 26 | 0.989 | 0.979 | 0.032 | 0.038 | 1 | **0.399** | **0.904** | **0.775** | 0.016 | 0.113 | -0.159 | 0.030 | 0.201 | 0.002 |
| | | | | | | | | 2 | **0.323** | -0.002 | 0.087 | **0.517** | **0.610** | **0.889** | **0.759** | **0.380** | **0.886** |
| | m3 | 1556 | 33 | - | - | - | - | - | | | | | | | | | |
| England | m1 | 1653 | 18 | 0.979 | 0.972 | 0.047 | 0.045 | 1 | **0.769** | **0.826** | **0.752** | **0.622** | **0.700** | **0.738** | **0.730** | **0.661** | **0.791** |
| | m2 | 1653 | 26 | 0.996 | 0.993 | 0.023 | 0.026 | 1 | **0.768** | **0.903** | **0.790** | **0.333** | **0.405** | -0.017 | **0.244** | **0.376** | 0.001 |
| | | | | | | | | 2 | 0.046 | -0.032 | -0.001 | **0.338** | **0.349** | **0.827** | **0.551** | **0.337** | **0.866** |
| | m3 | 1653 | 33 | - | - | - | - | - | | | | | | | | | |
| Estonia | m1 | 2311 | 18 | 0.974 | 0.966 | 0.043 | 0.050 | 1 | **0.774** | **0.784** | **0.723** | **0.570** | **0.595** | **0.634** | **0.722** | **0.552** | **0.736** |
| | m2 | 2311 | 26 | - | - | - | - | - | | | | | | | | | |
| | m3 | 2311 | 33 | - | - | - | - | - | | | | | | | | | |
| Finland | m1 | 1533 | 18 | 0.988 | 0.984 | 0.044 | 0.040 | 1 | **0.771** | **0.814** | **0.859** | **0.676** | **0.768** | **0.812** | **0.853** | **0.710** | **0.842** |
| | m2 | 1533 | 26 | - | - | - | - | - | | | | | | | | | |
| | m3 | 1533 | 33 | - | - | - | - | - | | | | | | | | | |
| France | m1 | 4310 | 18 | 0.982 | 0.976 | 0.032 | 0.036 | 1 | **0.741** | **0.788** | **0.761** | **0.527** | **0.649** | **0.697** | **0.706** | **0.605** | **0.729** |
| | m2 | 4310 | 26 | - | - | - | - | - | | | | | | | | | |
| | m3 | 4310 | 33 | - | - | - | - | - | | | | | | | | | |
| Georgia | m1 | 2033 | 18 | 0.977 | 0.969 | 0.031 | 0.041 | 1 | **0.539** | **0.660** | **0.717** | **0.595** | **0.610** | **0.698** | **0.790** | **0.740** | **0.812** |
| | m2 | 2033 | 26 | 0.991 | 0.984 | 0.023 | 0.029 | 1 | 0.129 | -0.001 | **0.456** | **0.424** | **0.590** | **0.725** | **0.662** | **0.593** | **0.904** |
| | | | | | | | | 2 | **0.496** | **0.848** | **0.329** | **0.222** | 0.046 | -0.005 | 0.177 | 0.197 | -0.066 |
| | m3 | 2033 | 33 | - | - | - | - | - | | | | | | | | | |
| Germany | m1 | 2063 | 18 | 0.976 | 0.968 | 0.037 | 0.042 | 1 | **0.664** | **0.710** | **0.718** | **0.550** | **0.572** | **0.697** | **0.719** | **0.607** | **0.740** |
| | m2 | 2063 | 26 | - | - | - | - | - | | | | | | | | | |
| | m3 | 2063 | 33 | - | - | - | - | - | | | | | | | | | |
| Greece | m1 | 1857 | 18 | 0.991 | 0.988 | 0.023 | 0.032 | 1 | **0.729** | **0.674** | **0.660** | **0.440** | **0.475** | **0.679** | **0.655** | **0.593** | **0.734** |
| | m2 | 1857 | 26 | - | - | - | - | - | | | | | | | | | |
| | m3 | 1857 | 33 | - | - | - | - | - | | | | | | | | | |
| Hungary | m1 | 1857 | 18 | 0.966 | 0.955 | 0.040 | 0.052 | 1 | **0.741** | **0.687** | **0.633** | **0.465** | **0.578** | **0.604** | **0.651** | **0.574** | **0.695** |
| | m2 | 1857 | 26 | - | - | - | - | - | | | | | | | | | |
| | m3 | 1857 | 33 | - | - | - | - | - | | | | | | | | | |

*Notes.* EFA = exploratory factor analysis; the EFA was conducted using the Mplus default settings for EFA with categorical indicators (using Oblique Geomin rotation, Weighted Least Square Means and Variance adjusted estimation, with a probit regression link); Par. = number of free parameters; CFI = comparative fit index; TLI = Tucker Lewis index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual; (1) = preoccupation; (2) = tolerance; (3) = withdrawal; (4) = persistence; (5) = displacement; (6) = problem; (7) = deception; (8) = escape; (9) = conflict; Models without results ('-') showed estimation problems. Boldface factor loadings denote significant factor loadings at $p < 0.05$; Dark gray cells denote factor loadings > 0.50.

**Table A3.4 (Continued)**

*EFA Factor Solutions, Calibration Samples, by Country (n = 111,254 in 44 Countries)*

| Country | Model | *n* | Model fit Par. | CFI | TLI | RMSEA | SRMR | Factor loadings Factor | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Iceland | m1 | 3346 | 18 | 0.991 | 0.988 | 0.032 | 0.035 | 1 | **0.748** | **0.810** | **0.843** | **0.616** | **0.798** | **0.813** | **0.807** | **0.743** | **0.872** |
| | m2 | 3346 | 26 | - | - | - | - | - | | | | | | | | | |
| | m3 | 3346 | 33 | - | - | - | - | - | | | | | | | | | |
| Ireland | m1 | 1814 | 18 | 0.968 | 0.958 | 0.055 | 0.052 | 1 | **0.668** | **0.781** | **0.763** | **0.503** | **0.624** | **0.743** | **0.716** | **0.621** | **0.817** |
| | m2 | 1814 | 26 | 0.995 | 0.991 | 0.026 | 0.024 | 1 | **0.635** | **0.819** | **0.849** | -0.071 | 0.050 | 0.037 | -0.190 | **0.212** | 0.029 |
| | | | | | | | | 2 | 0.089 | 0.032 | -0.014 | **0.591** | **0.598** | **0.734** | **0.934** | **0.443** | **0.824** |
| | m3 | 1814 | 33 | - | - | - | - | - | | | | | | | | | |
| Israel | m1 | 3567 | 18 | 0.966 | 0.955 | 0.037 | 0.043 | 1 | **0.487** | **0.661** | **0.733** | **0.546** | **0.661** | **0.712** | **0.759** | **0.673** | **0.813** |
| | m2 | 3567 | 26 | - | - | - | - | - | | | | | | | | | |
| | m3 | 3567 | 33 | - | - | - | - | - | | | | | | | | | |
| Italy | m1 | 2034 | 18 | 0.981 | 0.974 | 0.034 | 0.040 | 1 | **0.654** | **0.594** | **0.675** | **0.578** | **0.552** | **0.666** | **0.673** | **0.538** | **0.738** |
| | m2 | 2034 | 26 | - | - | - | - | - | | | | | | | | | |
| | m3 | 2034 | 33 | - | - | - | - | - | | | | | | | | | |
| Kazakhstan | m1 | 2244 | 18 | 0.979 | 0.973 | 0.035 | 0.041 | 1 | **0.675** | **0.736** | **0.703** | **0.713** | **0.708** | **0.754** | **0.771** | **0.681** | **0.787** |
| | m2 | 2244 | 26 | 0.994 | 0.989 | 0.022 | 0.026 | 1 | **0.356** | **0.322** | **0.471** | -0.023 | **0.515** | **0.391** | **0.853** | 0.016 | **0.826** |
| | | | | | | | | 2 | **0.375** | **0.476** | 0.290 | **0.808** | 0.252 | **0.426** | -0.023 | **0.724** | 0.017 |
| | m3 | 2244 | 33 | - | - | - | - | - | | | | | | | | | |
| Latvia | m1 | 2071 | 18 | 0.980 | 0.974 | 0.036 | 0.043 | 1 | **0.683** | **0.748** | **0.660** | **0.442** | **0.629** | **0.768** | **0.748** | **0.507** | **0.725** |
| | m2 | 2071 | 26 | 0.991 | 0.983 | 0.029 | 0.030 | 1 | -0.002 | **0.334** | **0.342** | **0.314** | **0.413** | **0.914** | **0.656** | **0.324** | **0.757** |
| | | | | | | | | 2 | **-0.823** | **-0.504** | **-0.392** | -0.169 | **-0.277** | 0.107 | -0.141 | **-0.233** | -0.006 |
| | m3 | 2071 | 33 | - | - | - | - | - | | | | | | | | | |
| Lithuania | m1 | 1842 | 18 | 0.974 | 0.966 | 0.045 | 0.047 | 1 | **0.786** | **0.771** | **0.786** | **0.615** | **0.704** | **0.709** | **0.792** | **0.603** | **0.784** |
| | m2 | 1842 | 26 | - | - | - | - | - | | | | | | | | | |
| | m3 | 1842 | 33 | - | - | - | - | - | | | | | | | | | |
| Luxembourg | m1 | 1944 | 18 | 0.980 | 0.973 | 0.033 | 0.042 | 1 | **0.721** | **0.678** | **0.657** | **0.507** | **0.570** | **0.660** | **0.622** | **0.510** | **0.682** |
| | m2 | 1944 | 26 | - | - | - | - | - | | | | | | | | | |
| | m3 | 1944 | 33 | - | - | - | - | - | | | | | | | | | |
| Malta | m1 | 1252 | 18 | 0.991 | 0.988 | 0.023 | 0.035 | 1 | **0.732** | **0.661** | **0.709** | **0.544** | **0.565** | **0.662** | **0.652** | **0.566** | **0.672** |
| | m2 | 1252 | 26 | - | - | - | - | - | | | | | | | | | |
| | m3 | 1252 | 33 | - | - | - | - | - | | | | | | | | | |
| Netherlands | m1 | 2289 | 18 | 0.992 | 0.989 | 0.019 | 0.034 | 1 | **0.487** | **0.728** | **0.702** | **0.550** | **0.579** | **0.717** | **0.727** | **0.578** | **0.780** |
| | m2 | 2289 | 26 | 0.997 | 0.994 | 0.013 | 0.025 | 1 | **0.362** | **0.674** | **0.790** | 0.126 | 0.176 | -0.004 | -0.033 | 0.237 | 0.140 |
| | | | | | | | | 2 | 0.161 | 0.110 | -0.006 | **0.450** | **0.432** | **0.750** | **0.789** | **0.372** | **0.672** |
| | m3 | 2289 | 33 | - | - | - | - | - | | | | | | | | | |

*Notes.* EFA = exploratory factor analysis; the EFA was conducted using the Mplus default settings for EFA with categorical indicators (using Oblique Geomin rotation, Weighted Least Square Means and Variance adjusted estimation, with a probit regression link); Par. = number of free parameters; CFI = comparative fit index; TLI = Tucker Lewis index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual; (1) = preoccupation; (2) = tolerance; (3) = withdrawal; (4) = persistence; (5) = displacement; (6) = problem; (7) = deception; (8) = escape; (9) = conflict; Models without results ('-') showed estimation problems. Boldface factor loadings denote significant factor loadings at $p < 0.05$; Dark gray cells denote factor loadings > 0.50.

**Table A3.4 (Continued)**

*EFA Factor Solutions, Calibration Samples, by Country (n = 111,254 in 44 Countries)*

| | | | Model fit | | | | | Factor loadings | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Country** | **Model** | ***n*** | **Par.** | **CFI** | **TLI** | **RMSEA** | **SRMR** | **Factor** | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** | **(7)** | **(8)** | **(9)** |
| North Macedonia | m1 | 2287 | 18 | 0.979 | 0.972 | 0.038 | 0.041 | 1 | **0.712** | **0.734** | **0.635** | **0.443** | **0.528** | **0.682** | **0.762** | **0.524** | **0.783** |
| | m2 | 2287 | 26 | 0.992 | 0.985 | 0.028 | 0.028 | 1 | **0.762** | **0.787** | **0.599** | **0.309** | 0.144 | -0.108 | 0.091 | **0.471** | -0.002 |
| | | | | | | | | 2 | -0.008 | -0.017 | 0.063 | 0.154 | **0.411** | **0.829** | **0.709** | 0.075 | **0.832** |
| | m3 | 2287 | 33 | - | - | - | - | - | | | | | | | | | |
| Norway | m1 | 1526 | 18 | 0.984 | 0.978 | 0.039 | 0.034 | 1 | **0.774** | **0.791** | **0.756** | **0.602** | **0.790** | **0.784** | **0.836** | **0.621** | **0.934** |
| | m2 | 1526 | 26 | - | - | - | - | - | | | | | | | | | |
| | m3 | 1526 | 33 | - | - | - | - | - | | | | | | | | | |
| Poland | m1 | 2527 | 18 | 0.980 | 0.973 | 0.038 | 0.045 | 1 | **0.728** | **0.682** | **0.672** | **0.593** | **0.635** | **0.676** | **0.696** | **0.584** | **0.698** |
| | m2 | 2527 | 26 | 0.992 | 0.985 | 0.028 | 0.029 | 1 | **0.724** | **0.802** | **0.712** | 0.213 | 0.014 | 0.004 | 0.041 | **0.332** | 0.005 |
| | | | | | | | | 2 | 0.049 | -0.073 | 0.009 | **0.411** | **0.652** | **0.710** | **0.692** | **0.283** | **0.730** |
| | m3 | 2527 | 33 | - | - | - | - | - | | | | | | | | | |
| Portugal | m1 | 2933 | 18 | 0.973 | 0.964 | 0.048 | 0.047 | 1 | **0.741** | **0.785** | **0.773** | **0.651** | **0.730** | **0.747** | **0.773** | **0.676** | **0.804** |
| | m2 | 2933 | 26 | - | - | - | - | - | | | | | | | | | |
| | m3 | 2933 | 33 | - | - | - | - | - | | | | | | | | | |
| Republic of Moldova | m1 | 2214 | 18 | 0.986 | 0.981 | 0.025 | 0.034 | 1 | **0.635** | **0.603** | **0.644** | **0.477** | **0.594** | **0.535** | **0.685** | **0.491** | **0.683** |
| | m2 | 2214 | 26 | - | - | - | - | - | | | | | | | | | |
| | m3 | 2214 | 33 | - | - | - | - | - | | | | | | | | | |
| Romania | m1 | 2241 | 18 | 0.982 | 0.976 | 0.032 | 0.038 | 1 | **0.573** | **0.664** | **0.678** | **0.418** | **0.607** | **0.667** | **0.706** | **0.553** | **0.715** |
| | m2 | 2241 | 26 | - | - | - | - | - | | | | | | | | | |
| | m3 | 2241 | 33 | - | - | - | - | - | | | | | | | | | |
| Russian Federation | m1 | 2030 | 18 | 0.990 | 0.986 | 0.033 | 0.034 | 1 | **0.757** | **0.803** | **0.767** | **0.708** | **0.692** | **0.759** | **0.845** | **0.709** | **0.785** |
| | m2 | 2030 | 26 | - | - | - | - | - | | | | | | | | | |
| | m3 | 2030 | 33 | - | - | - | - | - | | | | | | | | | |
| Scotland | m1 | 2458 | 18 | 0.972 | 0.963 | 0.045 | 0.054 | 1 | **0.699** | **0.802** | **0.752** | **0.580** | **0.707** | **0.739** | **0.733** | **0.647** | **0.788** |
| | m2 | 2458 | 26 | 0.997 | 0.995 | 0.017 | 0.025 | 1 | **0.612** | **0.959** | **0.538** | 0.077 | **0.241** | 0.060 | -0.032 | **0.195** | -0.014 |
| | | | | | | | | 2 | **0.174** | -0.004 | **0.297** | **0.555** | **0.531** | **0.733** | **0.805** | **0.511** | **0.844** |
| | m3 | 2458 | 33 | - | - | - | - | - | | | | | | | | | |
| Serbia | m1 | 1870 | 18 | 0.973 | 0.963 | 0.050 | 0.056 | 1 | **0.722** | **0.782** | **0.806** | **0.521** | **0.733** | **0.763** | **0.745** | **0.615** | **0.795** |
| | m2 | 1870 | 26 | 0.990 | 0.981 | 0.036 | 0.034 | 1 | **0.578** | **0.736** | **0.916** | 0.030 | **0.258** | 0.024 | -0.015 | 0.058 | -0.001 |
| | | | | | | | | 2 | **0.214** | 0.115 | -0.011 | **0.516** | **0.525** | **0.779** | **0.793** | **0.592** | **0.835** |
| | m3 | 1870 | 33 | 0.997 | 0.990 | 0.026 | 0.020 | 1 | **0.552** | **0.695** | **0.817** | 0.006 | **0.252** | 0.009 | 0.024 | -0.014 | -0.030 |
| Slovenia | m1 | 2563 | 18 | 0.990 | 0.986 | 0.029 | 0.033 | 1 | **0.752** | **0.802** | **0.775** | **0.488** | **0.704** | **0.775** | **0.757** | **0.694** | **0.794** |
| | m2 | 2563 | 26 | - | - | - | - | - | | | | | | | | | |
| | m3 | 2563 | 33 | - | - | - | - | - | | | | | | | | | |

*Notes.* EFA = exploratory factor analysis; the EFA was conducted using the Mplus default settings for EFA with categorical indicators (using Oblique Geomin rotation, Weighted Least Square Means and Variance adjusted estimation, with a probit regression link); Par. = number of free parameters; CFI = comparative fit index; TLI = Tucker Lewis index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual; (1) = preoccupation; (2) = tolerance; (3) = withdrawal; (4) = persistence; (5) = displacement; (6) = problem; (7) = deception; (8) = escape; (9) = conflict; Models without results ('-') showed estimation problems. Boldface factor loadings denote significant factor loadings at $p < 0.05$; Dark gray cells denote factor loadings > 0.50.

**Table A3.4 (Continued)**

*EFA Factor Solutions, Calibration Samples, by Country (n = 111,254 in 44 Countries)*

| | | | Model fit | | | | | Factor loadings | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Country** | **Model** | ***n*** | **Par.** | **CFI** | **TLI** | **RMSEA** | **SRMR** | **Factor** | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** | **(7)** | **(8)** | **(9)** |
| Spain | m1 | 2035 | 18 | 0.984 | 0.978 | 0.047 | 0.043 | 1 | **0.766** | **0.741** | **0.773** | **0.666** | **0.684** | **0.726** | **0.784** | **0.700** | **0.801** |
| | m2 | 2035 | 26 | - | - | - | - | - | | | | | | | | | |
| | m3 | 2035 | 33 | - | - | - | - | - | | | | | | | | | |
| Sweden | m1 | 2003 | 18 | 0.964 | 0.952 | 0.048 | 0.062 | 1 | **0.653** | **0.662** | **0.749** | **0.632** | **0.608** | **0.727** | **0.757** | **0.619** | **0.742** |
| | m2 | 2003 | 26 | - | - | - | - | - | | | | | | | | | |
| | m3 | 2003 | 33 | - | - | - | - | - | | | | | | | | | |
| Switzerland | m1 | 3561 | 18 | 0.988 | 0.984 | 0.023 | 0.030 | 1 | **0.705** | **0.712** | **0.635** | **0.476** | **0.520** | **0.647** | **0.600** | **0.554** | **0.658** |
| | m2 | 3561 | 26 | - | - | - | - | - | | | | | | | | | |
| | m3 | 3561 | 33 | - | - | - | - | - | | | | | | | | | |
| Turkey | m1 | 2770 | 18 | 0.987 | 0.982 | 0.032 | 0.035 | 1 | **0.682** | **0.623** | **0.661** | **0.630** | **0.636** | **0.740** | **0.725** | **0.625** | **0.750** |
| | m2 | 2770 | 26 | 0.995 | 0.990 | 0.024 | 0.023 | 1 | **0.426** | -0.007 | 0.227 | **0.309** | **0.697** | **0.710** | **0.700** | 0.154 | **0.789** |
| | | | | | | | | 2 | **0.301** | **0.714** | **0.495** | **0.366** | -0.041 | 0.060 | 0.054 | **0.531** | -0.010 |
| | m3 | 2770 | 33 | 0.999 | 0.997 | 0.013 | 0.013 | 1 | **0.363** | -0.082 | 0.010 | **0.249** | **0.671** | **0.807** | **0.702** | -0.002 | **0.802** |
| | | | | | | | | 2 | **0.313** | **0.656** | **0.626** | 0.351 | -0.009 | -0.031 | 0.054 | 0.556 | -0.015 |
| | | | | | | | | 3 | 0.042 | 0.120 | -0.033 | 0.217 | -0.043 | 0.178 | -0.160 | 0.399 | 0.004 |
| Ukraine | m1 | 3116 | 18 | 0.972 | 0.963 | 0.044 | 0.049 | 1 | **0.687** | **0.756** | **0.704** | **0.462** | **0.731** | **0.741** | **0.766** | **0.506** | **0.755** |
| | m2 | 3116 | 26 | - | - | - | - | - | | | | | | | | | |
| | m3 | 3116 | 33 | - | - | - | - | - | | | | | | | | | |
| Wales | m1 | 7728 | 18 | 0.980 | 0.974 | 0.048 | 0.039 | 1 | **0.767** | **0.827** | **0.792** | **0.655** | **0.740** | **0.744** | **0.785** | **0.658** | **0.815** |
| | m2 | 7728 | 26 | 0.997 | 0.995 | 0.022 | 0.018 | 1 | **0.771** | **0.917** | **0.700** | **0.284** | **0.292** | 0.002 | 0.064 | **0.244** | -0.059 |
| | | | | | | | | 2 | 0.043 | -0.033 | 0.143 | **0.409** | **0.490** | **0.785** | **0.763** | **0.452** | **0.912** |
| | m3 | 7728 | 33 | - | - | - | - | - | | | | | | | | | |

*Notes.* EFA = exploratory factor analysis; the EFA was conducted using the Mplus default settings for EFA with categorical indicators (using Oblique Geomin rotation, Weighted Least Square Means and Variance adjusted estimation, with a probit regression link); Par. = number of free parameters; CFI = comparative fit index; TLI = Tucker Lewis index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual; (1) = preoccupation; (2) = tolerance; (3) = withdrawal; (4) = persistence; (5) = displacement; (6) = problem; (7) = deception; (8) = escape; (9) = conflict; Models without results ('-') showed estimation problems. Boldface factor loadings denote significant factor loadings at $p < 0.05$; Dark gray cells denote factor loadings > 0.50.

3

## Summary EFA results (Tables A3.3 and A3.4)

We evaluated the EFAs based on empirical eigenvalues and parallel analysis using the calibration samples for each country. The number of factors with empirical eigenvalues higher than one denotes the number of potential factors to retain. We compared the empirical eigenvalues values with 1,000 randomly generated eigenvalues, based on the same number of items and sample size of the respective country. The number of factors to retain was determined by the number of factors where the 95$^{th}$ percentile random data eigenvalues did not exceed the empirical eigenvalues (Ledesma & Valero-Mora, 2007). In 42 out of 44 countries, results from the EFA identified one factor with an eigenvalue higher than one, suggesting a one-factor solution in these countries (Table A3.3). For Sweden and Ukraine, two factors showed an eigenvalue higher than one, suggesting a two-factor solution. However, the parallel analysis did not replicate this finding, because the empirical eigenvalue of only the first factor exceeded its 95$^{th}$ random eigenvalue. Thus, also in these two countries, a one-factor solution was supported.

Nevertheless, for each country, we estimated the model estimates from the one-, two-, and three-factor solutions. Model fit was evaluated based on the Comparative Fit Index (CFI), Tucker Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR) (CFI/TLI: ≥ 0.90 acceptable, ≥ 0.95 good; RMSEA: ≤ 0.08 acceptable, ≤ 0.06 good; SRMR: ≤ 0.10 acceptable, ≤ 0.08 good) (Hu & Bentler, 1999). We did not rely on the Chi-square statistic given its sensitivity to large sample sizes (Fabrigar et al., 1999).

In all 44 countries, the model fit of the one-factor solution was good according to all fit indices, because the lowest observed CFI and TLI were 0.964 and 0.952 and the highest RMSEA and SRMR 0.055 and 0.062, respectively (Table A3.4). We also evaluated the quality of the one-factor solution, whereby the quality of the factor was considered good when there were at least five items with significant ($p < 0.05$) factor loadings higher than 0.50 (Costello & Osborne, 2005). In all countries, this requirement was fulfilled (Table A3.4). More specifically, in 30 out of 44 countries, all nine factor loadings exceeded 0.50. In 12 countries, there was one factor loading lower than 0.50 (although not lower than 0.42), and in two countries, there were two factor loadings lower than 0.50 (although not lower than 0.44). Thus, in all countries, the model fit and quality of the one-factor model was good.

For 28 out of 44 countries, the two-factor solution yielded estimation problems. Often, these problems emerged because the two factors showed correlations equal or greater than one. Such model estimates should not be interpreted and warrant re-specification (Bagozzi & Yi, 1988). Hence, for these countries, the two-factor solutions were considered inappropriate. From the 16 countries that showed no estimation problems, the two-factor model showed better model fit than the one-factor model (Table A3.4). Subsequently, we evaluated the quality of the two-factor solutions, whereby each factor should consist of at least three items with significant ($p < 0.05$) factor loadings higher than 0.50 without any cross-loadings that differed less than 0.20 (Costello & Osborne, 2005; Howard, 2016). Six out of the 16 countries without estimation problems did not meet this requirement (Denmark, Georgia, Kazakhstan, Latvia, Netherlands, and Turkey), suggesting the quality of the two-factor solution was poor in these countries. Nine out of the 16 countries showed one factor with the items preoccupation, tolerance, and withdrawal and a second factor that was not consistent across countries (Canada, Croatia, England, Ireland, North Macedonia, Poland, Scotland, Serbia, and Wales). More specifically, after removal of items with factor loadings < 0.50 and cross-loadings, the second factor consisted of at least three of the items persistence, displacement, problem, deception, escape, and conflict. One out of the 16 countries showed one factor with items preoccupation, tolerance, withdrawal, and displacement and a second factor with items problems, deception, and conflict (Belgium: Flanders).

For 41 out of 44 countries, the three-factor solution yielded estimation problems, also mostly because factor correlations were equal or greater than one. Hence, the three-factor solution was considered inappropriate for these countries (Bagozzi & Yi, 1988). From the three countries that showed no estimation problems, the three-factor model showed better model fit than the one- and two-factor solution (Austria, Belgium: Flanders, and Turkey). However, the quality of the three-factor solutions was poor, because after removal of items with factor loadings < 0.50 and cross-loadings, the second and/or third factor consisted of less than three items (Table A3.4).

In sum, in 34 out of 44 countries, results from the eigenvalues and parallel analysis suggested a one-factor solution and, accordingly, the quality of the two- and three-factor solutions was poor. In the 10 other countries, the quality of the two-factor solution was acceptable, however, the eigenvalues and parallel analysis suggested a one-factor solution. As such, there was insufficient evidence for two-factor models. Furthermore, the model fit of the one-factor model was good in all countries, as well as the quality of the factor. Thus, we consider the factor structure as unidimensional.

**Table A3.5**

*CFA Model Fit and Reliability, Validation Samples, by Country (n = 111,278 in 44 Countries)*

| Country | *n* | CFI | TLI | RMSEA | SRMR | Min. loading[1] | Max. loading[2] | Internal consistency[3] |
|---|---|---|---|---|---|---|---|---|
| Albania | 825 | 0.988 | 0.984 | 0.029 | 0.040 | 0.470 | 0.763 | 0.867 |
| Armenia | 2215 | 0.994 | 0.991 | 0.022 | 0.030 | 0.606 | 0.765 | 0.900 |
| Austria | 2006 | 0.977 | 0.969 | 0.037 | 0.046 | 0.544 | 0.729 | 0.864 |
| Azerbaijan | 1889 | 0.980 | 0.973 | 0.040 | 0.039 | 0.754 | 0.874 | 0.951 |
| Belgium (Flanders) | 2059 | 0.976 | 0.968 | 0.039 | 0.044 | 0.501 | 0.774 | 0.872 |
| Belgium (Wallonia) | 2611 | 0.984 | 0.978 | 0.035 | 0.036 | 0.486 | 0.761 | 0.871 |
| Canada | 6178 | 0.975 | 0.967 | 0.031 | 0.046 | 0.598 | 0.834 | 0.907 |
| Croatia | 2457 | 0.978 | 0.970 | 0.047 | 0.042 | 0.602 | 0.828 | 0.911 |
| Czechia | 5581 | 0.979 | 0.972 | 0.038 | 0.043 | 0.560 | 0.799 | 0.899 |
| Denmark | 1557 | 0.973 | 0.965 | 0.044 | 0.057 | 0.568 | 0.806 | 0.900 |
| England | 1653 | 0.972 | 0.963 | 0.043 | 0.056 | 0.588 | 0.830 | 0.892 |
| Estonia | 2311 | 0.977 | 0.969 | 0.043 | 0.047 | 0.577 | 0.810 | 0.900 |
| Finland | 1534 | 0.982 | 0.976 | 0.044 | 0.044 | 0.664 | 0.857 | 0.924 |
| France | 4311 | 0.976 | 0.968 | 0.036 | 0.042 | 0.519 | 0.803 | 0.887 |
| Georgia | 2034 | 0.990 | 0.986 | 0.022 | 0.038 | 0.540 | 0.765 | 0.878 |
| Germany | 2063 | 0.986 | 0.981 | 0.028 | 0.037 | 0.544 | 0.713 | 0.867 |
| Greece | 1858 | 0.981 | 0.975 | 0.032 | 0.038 | 0.380 | 0.759 | 0.840 |
| Hungary | 1858 | 0.963 | 0.951 | 0.043 | 0.051 | 0.401 | 0.703 | 0.844 |
| Iceland | 3347 | 0.988 | 0.984 | 0.031 | 0.036 | 0.603 | 0.858 | 0.927 |
| Ireland | 1814 | 0.966 | 0.955 | 0.057 | 0.053 | 0.554 | 0.791 | 0.886 |
| Israel | 3567 | 0.979 | 0.972 | 0.032 | 0.037 | 0.527 | 0.832 | 0.889 |
| Italy | 2035 | 0.978 | 0.971 | 0.037 | 0.041 | 0.516 | 0.716 | 0.852 |
| Kazakhstan | 2244 | 0.986 | 0.981 | 0.030 | 0.039 | 0.632 | 0.810 | 0.913 |
| Latvia | 2072 | 0.984 | 0.978 | 0.033 | 0.041 | 0.428 | 0.801 | 0.872 |
| Lithuania | 1843 | 0.983 | 0.978 | 0.041 | 0.042 | 0.593 | 0.813 | 0.914 |
| Luxembourg | 1945 | 0.975 | 0.967 | 0.039 | 0.044 | 0.522 | 0.742 | 0.856 |
| Malta | 2288 | 0.977 | 0.969 | 0.038 | 0.042 | 0.451 | 0.775 | 0.859 |
| Netherlands | 1252 | 0.979 | 0.972 | 0.040 | 0.047 | 0.506 | 0.768 | 0.858 |
| North Macedonia | 2290 | 0.988 | 0.984 | 0.023 | 0.037 | 0.524 | 0.744 | 0.875 |
| Norway | 1527 | 0.987 | 0.983 | 0.035 | 0.032 | 0.603 | 0.930 | 0.934 |
| Poland | 2528 | 0.979 | 0.972 | 0.041 | 0.042 | 0.574 | 0.798 | 0.890 |
| Portugal | 2933 | 0.981 | 0.974 | 0.041 | 0.041 | 0.610 | 0.788 | 0.908 |
| Republic of Moldova | 2215 | 0.987 | 0.982 | 0.025 | 0.033 | 0.470 | 0.716 | 0.841 |
| Romania | 2242 | 0.987 | 0.983 | 0.028 | 0.031 | 0.430 | 0.712 | 0.848 |
| Russian Federation | 2031 | 0.990 | 0.986 | 0.035 | 0.032 | 0.694 | 0.826 | 0.927 |
| Scotland | 2458 | 0.968 | 0.958 | 0.051 | 0.060 | 0.561 | 0.837 | 0.900 |
| Serbia | 1870 | 0.983 | 0.978 | 0.042 | 0.042 | 0.603 | 0.804 | 0.910 |
| Slovenia | 2563 | 0.990 | 0.986 | 0.029 | 0.036 | 0.492 | 0.790 | 0.902 |
| Spain | 2035 | 0.986 | 0.981 | 0.040 | 0.036 | 0.604 | 0.809 | 0.906 |
| Sweden | 2003 | 0.978 | 0.970 | 0.045 | 0.048 | 0.603 | 0.793 | 0.896 |
| Switzerland | 3561 | 0.971 | 0.962 | 0.037 | 0.044 | 0.494 | 0.741 | 0.844 |
| Turkey | 2771 | 0.981 | 0.975 | 0.039 | 0.039 | 0.614 | 0.750 | 0.883 |
| Ukraine | 3116 | 0.979 | 0.972 | 0.038 | 0.042 | 0.481 | 0.786 | 0.885 |
| Wales | 7728 | 0.980 | 0.973 | 0.048 | 0.040 | 0.649 | 0.840 | 0.921 |

*Notes.* CFA = confirmatory factor analysis; SMU = social media use; CFI = comparative fit index; TLI = Tucker Lewis index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual.
[1] Lowest observed factor loading from nine items.
[2] Highest observed factor loading from nine items.
[3] Based on ordinal alpha.

**Table A3.6**

*CFA Factor Loadings Problematic SMU, Validation Samples, by Country (n = 111,278 in 44 Countries)*

| | | **Problematic SMU items** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | ***n*** | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** | **(7)** | **(8)** | **(9)** |
| Albania | 825 | 0.661 | 0.695 | 0.707 | 0.612 | 0.626 | *0.470* | **0.763** | 0.657 | 0.708 |
| Armenia | 2215 | 0.702 | 0.736 | 0.675 | *0.606* | 0.739 | 0.756 | **0.765** | 0.649 | 0.760 |
| Austria | 2006 | 0.725 | 0.675 | 0.695 | 0.565 | 0.567 | 0.650 | 0.700 | *0.544* | **0.729** |
| Azerbaijan | 1889 | *0.754* | 0.814 | 0.828 | 0.814 | 0.838 | 0.873 | 0.859 | 0.829 | **0.874** |
| Belgium (Flanders) | 2059 | 0.710 | **0.774** | 0.733 | *0.501* | 0.589 | 0.640 | 0.676 | 0.597 | 0.736 |
| Belgium (Wallonia) | 2611 | 0.660 | 0.733 | 0.721 | *0.486* | 0.589 | 0.666 | 0.720 | 0.582 | **0.761** |
| Canada | 6178 | 0.781 | **0.834** | 0.771 | 0.645 | 0.638 | 0.766 | 0.731 | *0.598* | 0.799 |
| Croatia | 2457 | 0.743 | 0.763 | 0.748 | *0.602* | 0.708 | 0.760 | 0.778 | 0.681 | **0.828** |
| Czechia | 5581 | 0.737 | **0.799** | 0.762 | *0.560* | 0.692 | 0.696 | 0.747 | 0.653 | 0.737 |
| Denmark | 1557 | 0.733 | 0.773 | 0.767 | 0.615 | 0.695 | 0.721 | 0.768 | *0.568* | **0.806** |
| England | 1653 | 0.671 | 0.760 | 0.735 | *0.588* | 0.620 | 0.735 | 0.722 | 0.641 | **0.830** |
| Estonia | 2311 | 0.795 | **0.810** | 0.708 | *0.577* | 0.668 | 0.758 | 0.758 | 0.595 | 0.760 |
| Finland | 1534 | 0.774 | **0.857** | 0.851 | 0.667 | 0.695 | 0.779 | 0.803 | *0.664* | 0.781 |
| France | 4311 | 0.737 | **0.803** | 0.738 | *0.519* | 0.643 | 0.696 | 0.678 | 0.589 | 0.772 |
| Georgia | 2034 | *0.540* | 0.631 | 0.711 | 0.593 | 0.601 | 0.703 | **0.765** | 0.725 | 0.760 |
| Germany | 2063 | 0.704 | 0.688 | 0.707 | *0.544* | 0.587 | 0.654 | **0.713** | 0.585 | 0.686 |
| Greece | 1858 | 0.659 | 0.637 | 0.604 | *0.380* | 0.523 | 0.648 | 0.689 | 0.608 | **0.759** |
| Hungary | 1858 | **0.703** | 0.673 | 0.682 | *0.401* | 0.619 | 0.627 | 0.617 | 0.571 | 0.694 |
| Iceland | 3347 | 0.805 | 0.813 | 0.817 | *0.603* | 0.770 | 0.770 | 0.786 | 0.716 | **0.858** |
| Ireland | 1814 | 0.682 | 0.761 | 0.744 | 0.585 | 0.632 | 0.715 | 0.725 | *0.554* | **0.791** |
| Israel | 3567 | *0.527* | 0.644 | 0.722 | 0.562 | 0.670 | 0.756 | 0.801 | 0.700 | **0.832** |
| Italy | 2035 | **0.716** | 0.630 | 0.695 | 0.551 | 0.546 | 0.635 | 0.654 | *0.516* | 0.713 |
| Kazakhstan | 2244 | *0.632* | 0.771 | 0.747 | 0.678 | 0.698 | 0.804 | 0.795 | 0.701 | **0.810** |
| Latvia | 2072 | 0.675 | 0.729 | 0.657 | *0.428* | 0.635 | **0.801** | 0.753 | 0.500 | 0.779 |
| Lithuania | 1843 | 0.798 | **0.813** | 0.792 | *0.593* | 0.720 | 0.752 | 0.809 | 0.629 | 0.758 |
| Luxembourg | 1945 | **0.742** | 0.682 | 0.659 | 0.539 | *0.522* | 0.687 | 0.654 | *0.522* | 0.709 |
| Malta | 2288 | 0.712 | 0.704 | 0.650 | *0.451* | 0.567 | 0.661 | **0.775** | 0.500 | 0.744 |
| Netherlands | 1252 | 0.671 | **0.768** | 0.742 | 0.508 | 0.614 | 0.656 | 0.641 | *0.506* | 0.617 |
| North Macedonia | 2290 | *0.524* | 0.736 | 0.725 | 0.596 | 0.628 | **0.744** | 0.719 | 0.579 | 0.738 |
| Norway | 1527 | 0.778 | 0.834 | 0.796 | *0.603* | 0.782 | 0.832 | 0.816 | 0.698 | **0.930** |
| Poland | 2528 | **0.798** | 0.735 | 0.747 | *0.574* | 0.673 | 0.704 | 0.701 | 0.575 | 0.727 |
| Portugal | 2933 | 0.734 | **0.788** | 0.780 | *0.610* | 0.732 | 0.743 | 0.759 | 0.629 | 0.781 |
| Republic of Moldova | 2215 | 0.636 | 0.633 | 0.653 | *0.470* | 0.586 | 0.602 | **0.716** | 0.497 | 0.712 |
| Romania | 2242 | 0.599 | 0.634 | 0.671 | *0.430* | 0.589 | 0.670 | 0.682 | 0.603 | **0.712** |
| Russian Federation | 2031 | 0.777 | **0.826** | 0.806 | 0.695 | 0.774 | 0.781 | 0.805 | *0.694* | 0.763 |
| Scotland | 2458 | 0.760 | **0.837** | 0.751 | 0.593 | 0.720 | 0.729 | 0.720 | *0.561* | 0.775 |
| Serbia | 1870 | 0.747 | 0.744 | 0.778 | *0.603* | 0.724 | 0.768 | 0.793 | 0.634 | **0.804** |
| Slovenia | 2563 | 0.758 | 0.770 | 0.746 | *0.492* | 0.671 | 0.757 | 0.761 | 0.690 | **0.790** |
| Spain | 2035 | 0.767 | 0.683 | 0.777 | *0.604* | 0.691 | 0.725 | 0.792 | 0.655 | **0.809** |
| Sweden | 2003 | 0.710 | 0.710 | 0.743 | *0.603* | 0.606 | 0.778 | 0.735 | 0.672 | **0.793** |
| Switzerland | 3561 | **0.741** | 0.683 | 0.686 | *0.494* | 0.509 | 0.701 | 0.589 | 0.496 | 0.659 |
| Turkey | 2771 | 0.647 | 0.668 | 0.689 | *0.614* | 0.655 | **0.750** | 0.718 | 0.636 | 0.736 |
| Ukraine | 3116 | 0.690 | **0.786** | 0.737 | *0.481* | 0.668 | 0.708 | 0.757 | 0.576 | 0.755 |
| Wales | 7728 | 0.768 | **0.840** | 0.790 | *0.649* | 0.748 | 0.753 | 0.775 | 0.676 | 0.811 |

*Notes.* SMU = social media use; (1) = preoccupation; (2) = tolerance; (3) = withdrawal; (4) = persistence; (5) = displacement; (6) = problem; (7) = deception; (8) = escape; (9) = conflict. Rates in italics indicate the row minimum with respect to the nine items; rates in boldface indicate the row maximum with respect to the nine items.

**Table A3.7**

*Gender Measurement Invariance, by Country (n = 222,532 in 44 Countries)*

| | Configural invariance[1] (par. = 36) | | | | Scalar invariance[2] (par. = 29) | | | | Change | |
|---|---|---|---|---|---|---|---|---|---|---|
| | CFI | TLI | RMSEA | SRMR | CFI | TLI | RMSEA | SRMR | ΔCFI | ΔRMSEA |
| Albania | 0.981 | 0.975 | 0.036 | 0.049 | 0.981 | 0.977 | 0.035 | 0.050 | 0.000 | -0.001 |
| Armenia | 0.989 | 0.985 | 0.030 | 0.039 | 0.987 | 0.984 | 0.030 | 0.040 | -0.002 | 0.000 |
| Austria | 0.982 | 0.977 | 0.030 | 0.039 | 0.978 | 0.975 | 0.032 | 0.042 | -0.004 | 0.002 |
| Azerbaijan | 0.977 | 0.970 | 0.044 | 0.046 | 0.977 | 0.972 | 0.042 | 0.046 | 0.000 | -0.002 |
| Belgium (Flanders) | 0.980 | 0.973 | 0.037 | 0.043 | 0.975 | 0.971 | 0.039 | 0.046 | -0.005 | 0.002 |
| Belgium (Wallonia) | 0.982 | 0.976 | 0.037 | 0.038 | 0.981 | 0.977 | 0.036 | 0.039 | -0.001 | -0.001 |
| Canada | 0.971 | 0.962 | 0.032 | 0.049 | 0.973 | 0.968 | 0.029 | 0.049 | 0.002 | -0.003 |
| Croatia | 0.977 | 0.969 | 0.049 | 0.045 | 0.976 | 0.971 | 0.048 | 0.046 | -0.001 | -0.001 |
| Czechia | 0.978 | 0.970 | 0.038 | 0.043 | 0.976 | 0.972 | 0.037 | 0.045 | -0.002 | -0.001 |
| Denmark | 0.978 | 0.970 | 0.040 | 0.053 | 0.974 | 0.969 | 0.041 | 0.055 | -0.004 | 0.001 |
| England | 0.974 | 0.965 | 0.046 | 0.051 | 0.970 | 0.965 | 0.046 | 0.053 | -0.004 | 0.000 |
| Estonia | 0.974 | 0.965 | 0.045 | 0.050 | 0.973 | 0.968 | 0.043 | 0.051 | -0.001 | -0.002 |
| Finland | 0.985 | 0.980 | 0.044 | 0.043 | 0.982 | 0.979 | 0.046 | 0.044 | -0.003 | 0.002 |
| France | 0.975 | 0.966 | 0.036 | 0.040 | 0.974 | 0.969 | 0.034 | 0.041 | -0.001 | -0.002 |
| Georgia | 0.981 | 0.975 | 0.029 | 0.046 | 0.981 | 0.978 | 0.027 | 0.046 | 0.000 | -0.002 |
| Germany | 0.979 | 0.972 | 0.034 | 0.044 | 0.978 | 0.974 | 0.033 | 0.045 | -0.001 | -0.001 |
| Greece | 0.988 | 0.984 | 0.027 | 0.035 | 0.982 | 0.979 | 0.030 | 0.038 | -0.006 | 0.003 |
| Hungary | 0.968 | 0.957 | 0.039 | 0.050 | 0.962 | 0.955 | 0.040 | 0.053 | -0.006 | 0.001 |
| Iceland | 0.990 | 0.987 | 0.031 | 0.036 | 0.990 | 0.988 | 0.030 | 0.036 | 0.000 | -0.001 |
| Ireland | 0.967 | 0.956 | 0.055 | 0.053 | 0.963 | 0.956 | 0.055 | 0.054 | -0.004 | 0.000 |
| Israel | 0.972 | 0.963 | 0.034 | 0.040 | 0.970 | 0.965 | 0.034 | 0.042 | -0.002 | 0.000 |
| Italy | 0.979 | 0.971 | 0.036 | 0.042 | 0.980 | 0.976 | 0.033 | 0.043 | 0.001 | -0.003 |
| Kazakhstan | 0.983 | 0.977 | 0.034 | 0.043 | 0.983 | 0.980 | 0.032 | 0.044 | 0.000 | -0.002 |
| Latvia | 0.980 | 0.973 | 0.035 | 0.043 | 0.981 | 0.978 | 0.032 | 0.043 | 0.001 | -0.003 |
| Lithuania | 0.979 | 0.971 | 0.044 | 0.047 | 0.979 | 0.975 | 0.041 | 0.048 | 0.000 | -0.003 |
| Luxembourg | 0.977 | 0.970 | 0.036 | 0.044 | 0.977 | 0.973 | 0.034 | 0.045 | 0.000 | -0.002 |
| Malta | 0.985 | 0.980 | 0.031 | 0.042 | 0.983 | 0.980 | 0.030 | 0.043 | -0.002 | -0.001 |
| Netherlands | 0.990 | 0.986 | 0.021 | 0.037 | 0.991 | 0.989 | 0.018 | 0.038 | 0.001 | -0.003 |
| North Macedonia | 0.979 | 0.972 | 0.036 | 0.041 | 0.977 | 0.973 | 0.036 | 0.043 | -0.002 | 0.000 |
| Norway | 0.986 | 0.982 | 0.037 | 0.035 | 0.985 | 0.982 | 0.037 | 0.035 | -0.001 | 0.000 |
| Poland | 0.975 | 0.967 | 0.041 | 0.046 | 0.977 | 0.973 | 0.038 | 0.046 | 0.002 | -0.003 |
| Portugal | 0.976 | 0.967 | 0.046 | 0.045 | 0.973 | 0.969 | 0.045 | 0.045 | -0.003 | -0.001 |
| Republic of Moldova | 0.981 | 0.975 | 0.029 | 0.038 | 0.981 | 0.978 | 0.027 | 0.039 | 0.000 | -0.002 |
| Romania | 0.982 | 0.976 | 0.033 | 0.037 | 0.982 | 0.978 | 0.032 | 0.038 | 0.000 | -0.001 |
| Russian Federation | 0.989 | 0.986 | 0.035 | 0.033 | 0.988 | 0.986 | 0.034 | 0.034 | -0.001 | -0.001 |
| Scotland | 0.971 | 0.961 | 0.048 | 0.055 | 0.970 | 0.965 | 0.046 | 0.056 | -0.001 | -0.002 |
| Serbia | 0.975 | 0.967 | 0.049 | 0.053 | 0.975 | 0.971 | 0.046 | 0.054 | 0.000 | -0.003 |
| Slovenia | 0.985 | 0.980 | 0.034 | 0.038 | 0.986 | 0.983 | 0.031 | 0.039 | 0.001 | -0.003 |
| Spain | 0.982 | 0.976 | 0.047 | 0.042 | 0.982 | 0.978 | 0.044 | 0.042 | 0.000 | -0.003 |
| Sweden | 0.967 | 0.956 | 0.047 | 0.056 | 0.965 | 0.958 | 0.045 | 0.057 | -0.002 | -0.002 |
| Switzerland | 0.981 | 0.975 | 0.029 | 0.037 | 0.978 | 0.973 | 0.030 | 0.040 | -0.003 | 0.001 |
| Turkey | 0.981 | 0.975 | 0.038 | 0.038 | 0.980 | 0.977 | 0.036 | 0.039 | -0.001 | -0.002 |
| Ukraine | 0.973 | 0.964 | 0.043 | 0.047 | 0.974 | 0.969 | 0.040 | 0.047 | 0.001 | -0.003 |
| Wales | 0.979 | 0.973 | 0.047 | 0.040 | 0.977 | 0.973 | 0.046 | 0.041 | -0.002 | -0.001 |

*Notes.* SMU = social media use; par. = number of free parameters; CFI = comparative fit index; TLI = Tucker Lewis index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual.
[1] Item thresholds and factor loadings were allowed to vary across boys and girls.
[2] Item thresholds and factor loadings were constrained to be equal across boys and girls.

**Table A3.8**

*Age Measurement Invariance, by Country (n = 221,093 in 44 countries)*

| | Configural invariance[1] (par. = 54) | | | | Scalar invariance[2] (par. = 40) | | | | Change | |
|---|---|---|---|---|---|---|---|---|---|---|
| | CFI | TLI | RMSEA | SRMR | CFI | TLI | RMSEA | SRMR | ΔCFI | ΔRMSEA |
| Albania | 0.988 | 0.985 | 0.027 | 0.054 | 0.982 | 0.979 | 0.031 | 0.058 | -0.006 | 0.004 |
| Armenia | 0.989 | 0.986 | 0.027 | 0.039 | 0.989 | 0.988 | 0.025 | 0.041 | 0.000 | -0.002 |
| Austria | 0.983 | 0.978 | 0.029 | 0.043 | 0.983 | 0.981 | 0.027 | 0.045 | 0.000 | -0.002 |
| Azerbaijan | 0.982 | 0.976 | 0.059 | 0.080 | 0.980 | 0.978 | 0.057 | 0.080 | -0.002 | -0.002 |
| Belgium (Flanders) | 0.978 | 0.971 | 0.038 | 0.047 | 0.978 | 0.975 | 0.035 | 0.048 | 0.000 | -0.003 |
| Belgium (Wallonia) | 0.980 | 0.973 | 0.038 | 0.042 | 0.976 | 0.973 | 0.038 | 0.045 | -0.004 | 0.000 |
| Canada | 0.967 | 0.956 | 0.032 | 0.052 | 0.968 | 0.963 | 0.030 | 0.053 | 0.001 | -0.002 |
| Croatia | 0.978 | 0.970 | 0.047 | 0.046 | 0.976 | 0.972 | 0.045 | 0.047 | -0.002 | -0.002 |
| Czechia | 0.978 | 0.971 | 0.037 | 0.044 | 0.978 | 0.975 | 0.035 | 0.045 | 0.000 | -0.002 |
| Denmark | 0.975 | 0.966 | 0.042 | 0.060 | 0.976 | 0.973 | 0.038 | 0.062 | 0.001 | -0.004 |
| England | 0.976 | 0.968 | 0.043 | 0.052 | 0.976 | 0.973 | 0.039 | 0.054 | 0.000 | -0.004 |
| Estonia | 0.973 | 0.964 | 0.045 | 0.054 | 0.969 | 0.965 | 0.044 | 0.057 | -0.004 | -0.001 |
| Finland | 0.988 | 0.984 | 0.039 | 0.046 | 0.988 | 0.986 | 0.037 | 0.046 | 0.000 | -0.002 |
| France | 0.978 | 0.971 | 0.033 | 0.041 | 0.977 | 0.974 | 0.032 | 0.043 | -0.001 | -0.001 |
| Georgia | 0.984 | 0.979 | 0.023 | 0.044 | 0.984 | 0.982 | 0.022 | 0.045 | 0.000 | -0.001 |
| Germany | 0.983 | 0.977 | 0.031 | 0.043 | 0.982 | 0.980 | 0.029 | 0.045 | -0.001 | -0.002 |
| Greece | 0.985 | 0.980 | 0.027 | 0.041 | 0.980 | 0.977 | 0.029 | 0.045 | -0.005 | 0.002 |
| Hungary | 0.963 | 0.951 | 0.041 | 0.057 | 0.959 | 0.953 | 0.040 | 0.061 | -0.004 | -0.001 |
| Iceland | 0.989 | 0.986 | 0.033 | 0.039 | 0.989 | 0.988 | 0.030 | 0.039 | 0.000 | -0.003 |
| Ireland | 0.966 | 0.955 | 0.054 | 0.055 | 0.964 | 0.959 | 0.052 | 0.057 | -0.002 | -0.002 |
| Israel | 0.974 | 0.965 | 0.033 | 0.041 | 0.976 | 0.972 | 0.029 | 0.042 | 0.002 | -0.004 |
| Italy | 0.978 | 0.971 | 0.035 | 0.046 | 0.976 | 0.973 | 0.034 | 0.047 | -0.002 | -0.001 |
| Kazakhstan | 0.982 | 0.976 | 0.032 | 0.047 | 0.982 | 0.980 | 0.029 | 0.049 | 0.000 | -0.003 |
| Latvia | 0.981 | 0.974 | 0.034 | 0.045 | 0.979 | 0.976 | 0.033 | 0.048 | -0.002 | -0.001 |
| Lithuania | 0.978 | 0.971 | 0.045 | 0.051 | 0.979 | 0.976 | 0.041 | 0.052 | 0.001 | -0.004 |
| Luxembourg | 0.978 | 0.970 | 0.036 | 0.045 | 0.977 | 0.974 | 0.033 | 0.047 | -0.001 | -0.003 |
| Malta | 0.985 | 0.980 | 0.029 | 0.043 | 0.972 | 0.968 | 0.037 | 0.048 | -0.013 | 0.008 |
| Netherlands | 0.989 | 0.986 | 0.021 | 0.044 | 0.990 | 0.989 | 0.018 | 0.048 | 0.001 | -0.003 |
| North Macedonia | 0.976 | 0.968 | 0.035 | 0.045 | 0.975 | 0.972 | 0.033 | 0.047 | -0.001 | -0.002 |
| Norway | 0.980 | 0.973 | 0.038 | 0.038 | 0.979 | 0.976 | 0.037 | 0.039 | -0.001 | -0.001 |
| Poland | 0.977 | 0.969 | 0.040 | 0.048 | 0.976 | 0.972 | 0.037 | 0.049 | -0.001 | -0.003 |
| Portugal | 0.977 | 0.970 | 0.043 | 0.046 | 0.975 | 0.971 | 0.043 | 0.048 | -0.002 | 0.000 |
| Republic of Moldova | 0.978 | 0.971 | 0.029 | 0.043 | 0.977 | 0.974 | 0.028 | 0.045 | -0.001 | -0.001 |
| Romania | 0.986 | 0.981 | 0.029 | 0.038 | 0.979 | 0.976 | 0.033 | 0.041 | -0.007 | 0.004 |
| Russian Federation | 0.989 | 0.986 | 0.033 | 0.035 | 0.987 | 0.985 | 0.034 | 0.037 | -0.002 | 0.001 |
| Scotland | 0.970 | 0.960 | 0.046 | 0.059 | 0.971 | 0.967 | 0.041 | 0.059 | 0.001 | -0.005 |
| Serbia | 0.979 | 0.971 | 0.043 | 0.052 | 0.979 | 0.976 | 0.039 | 0.053 | 0.000 | -0.004 |
| Slovenia | 0.985 | 0.981 | 0.032 | 0.042 | 0.985 | 0.983 | 0.030 | 0.045 | 0.000 | -0.002 |
| Spain | 0.983 | 0.977 | 0.045 | 0.042 | 0.981 | 0.978 | 0.044 | 0.044 | -0.002 | -0.001 |
| Sweden | 0.971 | 0.962 | 0.044 | 0.056 | 0.973 | 0.969 | 0.039 | 0.058 | 0.002 | -0.005 |
| Switzerland | 0.979 | 0.972 | 0.031 | 0.041 | 0.978 | 0.975 | 0.029 | 0.043 | -0.001 | -0.002 |
| Turkey | 0.978 | 0.971 | 0.040 | 0.044 | 0.977 | 0.974 | 0.038 | 0.045 | -0.001 | -0.002 |
| Ukraine | 0.976 | 0.968 | 0.040 | 0.048 | 0.974 | 0.970 | 0.039 | 0.050 | -0.002 | -0.001 |
| Wales | 0.981 | 0.975 | 0.046 | 0.041 | 0.980 | 0.978 | 0.043 | 0.041 | -0.001 | -0.003 |

*Notes.* SMU = social media use; par. = number of free parameters; CFI = comparative fit index; TLI = Tucker Lewis index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual. The sample size refers to the complete data on age, as multiple CFA can only be conducted on complete data on the grouping variable (age).

[1] Item thresholds and factor loadings were allowed to vary across 11-, 13-, and 15-year-olds.

[2] Item thresholds and factor loadings were constrained to be equal across 11-, 13-, and 15-year-olds.

**Table A3.9**

*Socioeconomic Measurement Invariance, by Country (n = 212,353 in 44 Countries)*

| | Configural invariance[1] (par. = 54) | | | | Scalar invariance[2] (par. = 40) | | | | Change | |
|---|---|---|---|---|---|---|---|---|---|---|
| | CFI | TLI | RMSEA | SRMR | CFI | TLI | RMSEA | SRMR | ΔCFI | ΔRMSEA |
| Albania | 0.992 | 0.989 | 0.025 | 0.047 | 0.991 | 0.990 | 0.023 | 0.049 | -0.001 | -0.002 |
| Armenia | 0.988 | 0.984 | 0.030 | 0.040 | 0.989 | 0.988 | 0.026 | 0.040 | 0.001 | -0.004 |
| Austria | 0.984 | 0.978 | 0.030 | 0.045 | 0.985 | 0.983 | 0.026 | 0.047 | 0.001 | -0.004 |
| Azerbaijan | 0.977 | 0.969 | 0.049 | 0.060 | 0.977 | 0.974 | 0.045 | 0.062 | 0.000 | -0.004 |
| Belgium (Flanders) | 0.980 | 0.973 | 0.037 | 0.045 | 0.982 | 0.980 | 0.032 | 0.046 | 0.002 | -0.005 |
| Belgium (Wallonia) | 0.982 | 0.976 | 0.037 | 0.041 | 0.983 | 0.980 | 0.033 | 0.043 | 0.001 | -0.004 |
| Canada | 0.974 | 0.965 | 0.034 | 0.052 | 0.973 | 0.970 | 0.032 | 0.054 | -0.001 | -0.002 |
| Croatia | 0.978 | 0.970 | 0.047 | 0.047 | 0.978 | 0.975 | 0.043 | 0.047 | 0.000 | -0.004 |
| Czechia | 0.977 | 0.969 | 0.038 | 0.044 | 0.978 | 0.975 | 0.034 | 0.045 | 0.001 | -0.004 |
| Denmark | 0.973 | 0.964 | 0.044 | 0.063 | 0.977 | 0.973 | 0.038 | 0.063 | 0.004 | -0.006 |
| England | 0.975 | 0.967 | 0.045 | 0.054 | 0.976 | 0.972 | 0.041 | 0.055 | 0.001 | -0.004 |
| Estonia | 0.978 | 0.971 | 0.041 | 0.050 | 0.981 | 0.978 | 0.036 | 0.051 | 0.003 | -0.005 |
| Finland | 0.987 | 0.983 | 0.040 | 0.043 | 0.987 | 0.986 | 0.037 | 0.044 | 0.000 | -0.003 |
| France | 0.977 | 0.969 | 0.036 | 0.044 | 0.979 | 0.976 | 0.032 | 0.045 | 0.002 | -0.004 |
| Georgia | 0.986 | 0.981 | 0.025 | 0.045 | 0.987 | 0.985 | 0.022 | 0.046 | 0.001 | -0.003 |
| Germany | 0.982 | 0.976 | 0.032 | 0.044 | 0.984 | 0.982 | 0.028 | 0.045 | 0.002 | -0.004 |
| Greece | 0.985 | 0.980 | 0.029 | 0.040 | 0.985 | 0.983 | 0.027 | 0.042 | 0.000 | -0.002 |
| Hungary | 0.962 | 0.949 | 0.041 | 0.057 | 0.967 | 0.962 | 0.036 | 0.059 | 0.005 | -0.005 |
| Iceland | 0.993 | 0.990 | 0.028 | 0.036 | 0.993 | 0.992 | 0.026 | 0.036 | 0.000 | -0.002 |
| Ireland | 0.966 | 0.955 | 0.056 | 0.057 | 0.966 | 0.961 | 0.052 | 0.057 | 0.000 | -0.004 |
| Israel | 0.973 | 0.964 | 0.035 | 0.041 | 0.973 | 0.970 | 0.032 | 0.043 | 0.000 | -0.003 |
| Italy | 0.979 | 0.973 | 0.036 | 0.045 | 0.982 | 0.980 | 0.031 | 0.045 | 0.003 | -0.005 |
| Kazakhstan | 0.981 | 0.975 | 0.034 | 0.048 | 0.980 | 0.977 | 0.033 | 0.050 | -0.001 | -0.001 |
| Latvia | 0.983 | 0.977 | 0.033 | 0.043 | 0.985 | 0.983 | 0.028 | 0.044 | 0.002 | -0.005 |
| Lithuania | 0.980 | 0.973 | 0.043 | 0.049 | 0.982 | 0.979 | 0.038 | 0.050 | 0.002 | -0.005 |
| Luxembourg | 0.976 | 0.967 | 0.037 | 0.048 | 0.975 | 0.971 | 0.035 | 0.050 | -0.001 | -0.002 |
| Malta | 0.989 | 0.985 | 0.027 | 0.044 | 0.989 | 0.988 | 0.024 | 0.045 | 0.000 | -0.003 |
| Netherlands | 0.987 | 0.983 | 0.023 | 0.044 | 0.989 | 0.988 | 0.020 | 0.045 | 0.002 | -0.003 |
| North Macedonia | 0.976 | 0.967 | 0.038 | 0.046 | 0.976 | 0.973 | 0.035 | 0.047 | 0.000 | -0.003 |
| Norway | 0.987 | 0.982 | 0.037 | 0.037 | 0.987 | 0.985 | 0.034 | 0.038 | 0.000 | -0.003 |
| Poland | 0.978 | 0.971 | 0.041 | 0.048 | 0.980 | 0.977 | 0.036 | 0.049 | 0.002 | -0.005 |
| Portugal | 0.977 | 0.970 | 0.044 | 0.045 | 0.979 | 0.976 | 0.039 | 0.046 | 0.002 | -0.005 |
| Republic of Moldova | 0.986 | 0.981 | 0.025 | 0.037 | 0.987 | 0.985 | 0.023 | 0.039 | 0.001 | -0.002 |
| Romania | 0.984 | 0.978 | 0.032 | 0.040 | 0.985 | 0.983 | 0.028 | 0.040 | 0.001 | -0.004 |
| Russian Federation | 0.990 | 0.987 | 0.033 | 0.036 | 0.991 | 0.990 | 0.029 | 0.036 | 0.001 | -0.004 |
| Scotland | 0.972 | 0.963 | 0.047 | 0.057 | 0.972 | 0.968 | 0.043 | 0.058 | 0.000 | -0.004 |
| Serbia | 0.977 | 0.970 | 0.046 | 0.053 | 0.979 | 0.976 | 0.041 | 0.053 | 0.002 | -0.005 |
| Slovenia | 0.990 | 0.986 | 0.029 | 0.037 | 0.991 | 0.990 | 0.025 | 0.038 | 0.001 | -0.004 |
| Spain | 0.984 | 0.979 | 0.045 | 0.042 | 0.984 | 0.982 | 0.041 | 0.042 | 0.000 | -0.004 |
| Sweden | 0.971 | 0.961 | 0.046 | 0.058 | 0.969 | 0.965 | 0.044 | 0.061 | -0.002 | -0.002 |
| Switzerland | 0.978 | 0.970 | 0.032 | 0.042 | 0.979 | 0.976 | 0.029 | 0.044 | 0.001 | -0.003 |
| Turkey | 0.985 | 0.980 | 0.035 | 0.039 | 0.986 | 0.984 | 0.031 | 0.039 | 0.001 | -0.004 |
| Ukraine | 0.976 | 0.968 | 0.040 | 0.046 | 0.977 | 0.974 | 0.036 | 0.047 | 0.001 | -0.004 |
| Wales | 0.981 | 0.975 | 0.048 | 0.040 | 0.981 | 0.978 | 0.044 | 0.041 | 0.000 | -0.004 |

*Notes.* SMU = social media use; par. = number of free parameters; CFI = comparative fit index; TLI = Tucker Lewis index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual. The sample size refers to the complete data on socioeconomic status, as multiple CFA can only be conducted on complete data on the grouping variable (socioeconomic status).

[1] Item thresholds and factor loadings were allowed to vary across adolescents with low, moderate, and high socioeconomic status.

[2] Item thresholds and factor loadings were constrained to be equal across adolescents with low, moderate, and high socioeconomic status.

**Table A3.10**

*Life Satisfaction, by Problematic SMU and Country (n = 222,532 in 44 Countries)*

| | Means, total | | | Means, non-problematic | | | Means, problematic | | | Effect size mean differences | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Mean** | **95% LL** | **95% UL** | **Mean** | **95% LL** | **95% UL** | **Mean** | **95% LL** | **95% UL** | ***β*** | ***SE*** | ***p*** |
| Albania | 8.15 | 8.05 | 8.25 | 8.22 | 8.12 | 8.33 | 7.61 | 7.29 | 7.93 | -0.193 | 0.084 | 0.021 |
| Armenia | 8.34 | 8.29 | 8.39 | 8.37 | 8.31 | 8.42 | 7.94 | 7.66 | 8.22 | -0.242 | 0.073 | 0.001 |
| Austria | 7.70 | 7.64 | 7.77 | 7.76 | 7.70 | 7.82 | 6.58 | 6.20 | 6.96 | -0.517 | 0.092 | <0.001 |
| Azerbaijan | 8.34 | 8.27 | 8.40 | 8.34 | 8.28 | 8.41 | 8.30 | 8.07 | 8.52 | -0.118 | 0.076 | 0.121 |
| Belgium (Flanders) | 7.79 | 7.75 | 7.84 | 7.84 | 7.80 | 7.88 | 7.15 | 6.94 | 7.36 | -0.428 | 0.072 | <0.001 |
| Belgium (Wallonia) | 7.55 | 7.50 | 7.60 | 7.62 | 7.57 | 7.68 | 6.73 | 6.51 | 6.94 | -0.455 | 0.061 | <0.001 |
| Canada | 7.30 | 7.25 | 7.35 | 7.38 | 7.32 | 7.43 | 6.13 | 5.84 | 6.42 | -0.551 | 0.071 | <0.001 |
| Croatia | 8.09 | 8.04 | 8.14 | 8.18 | 8.13 | 8.24 | 7.24 | 7.03 | 7.44 | -0.461 | 0.058 | <0.001 |
| Czechia | 7.79 | 7.75 | 7.82 | 7.83 | 7.80 | 7.86 | 7.00 | 6.81 | 7.19 | -0.423 | 0.057 | <0.001 |
| Denmark | 7.68 | 7.62 | 7.74 | 7.72 | 7.66 | 7.78 | 6.71 | 6.34 | 7.07 | -0.536 | 0.104 | <0.001 |
| England | 7.44 | 7.37 | 7.51 | 7.55 | 7.48 | 7.62 | 6.14 | 5.82 | 6.46 | -0.682 | 0.092 | <0.001 |
| Estonia | 7.72 | 7.66 | 7.77 | 7.78 | 7.73 | 7.83 | 6.73 | 6.43 | 7.02 | -0.550 | 0.085 | <0.001 |
| Finland | 7.83 | 7.77 | 7.90 | 7.93 | 7.86 | 7.99 | 7.01 | 6.73 | 7.30 | -0.466 | 0.088 | <0.001 |
| France | 7.65 | 7.61 | 7.70 | 7.72 | 7.67 | 7.76 | 6.89 | 6.70 | 7.08 | -0.433 | 0.058 | <0.001 |
| Georgia | 7.99 | 7.93 | 8.05 | 8.00 | 7.93 | 8.06 | 7.81 | 7.49 | 8.13 | -0.089 | 0.101 | 0.374 |
| Germany | 7.68 | 7.63 | 7.73 | 7.71 | 7.65 | 7.76 | 7.14 | 6.78 | 7.49 | -0.324 | 0.099 | 0.001 |
| Greece | 7.52 | 7.46 | 7.58 | 7.63 | 7.57 | 7.70 | 6.49 | 6.26 | 6.71 | -0.475 | 0.058 | <0.001 |
| Hungary | 7.59 | 7.52 | 7.65 | 7.65 | 7.58 | 7.71 | 6.53 | 6.19 | 6.86 | -0.560 | 0.086 | <0.001 |
| Iceland | 7.61 | 7.56 | 7.65 | 7.66 | 7.61 | 7.70 | 6.57 | 6.27 | 6.87 | -0.515 | 0.074 | <0.001 |
| Ireland | 7.52 | 7.46 | 7.58 | 7.63 | 7.56 | 7.69 | 6.76 | 6.57 | 6.95 | -0.371 | 0.058 | <0.001 |
| Israel | 7.81 | 7.75 | 7.87 | 7.87 | 7.81 | 7.93 | 6.64 | 6.11 | 7.18 | -0.478 | 0.113 | <0.001 |
| Italy | 7.58 | 7.52 | 7.64 | 7.68 | 7.62 | 7.73 | 6.79 | 6.59 | 6.99 | -0.480 | 0.056 | <0.001 |
| Kazakhstan | 8.55 | 8.50 | 8.60 | 8.56 | 8.51 | 8.62 | 8.28 | 7.99 | 8.58 | -0.141 | 0.080 | 0.079 |
| Latvia | 7.39 | 7.33 | 7.45 | 7.45 | 7.39 | 7.51 | 6.31 | 6.00 | 6.62 | -0.529 | 0.087 | <0.001 |
| Lithuania | 7.91 | 7.85 | 7.97 | 7.97 | 7.91 | 8.04 | 7.14 | 6.86 | 7.41 | -0.437 | 0.068 | <0.001 |
| Luxembourg | 7.63 | 7.58 | 7.69 | 7.68 | 7.63 | 7.74 | 7.01 | 6.72 | 7.29 | -0.342 | 0.079 | <0.001 |
| Malta | 7.30 | 7.22 | 7.38 | 7.40 | 7.31 | 7.49 | 6.79 | 6.58 | 7.00 | -0.247 | 0.061 | <0.001 |
| Netherlands | 7.77 | 7.73 | 7.82 | 7.81 | 7.76 | 7.86 | 6.71 | 6.34 | 7.08 | -0.627 | 0.110 | <0.001 |
| North Macedonia | 8.42 | 8.36 | 8.48 | 8.51 | 8.45 | 8.57 | 7.59 | 7.36 | 7.82 | -0.368 | 0.061 | <0.001 |
| Norway | 7.89 | 7.83 | 7.96 | 7.94 | 7.88 | 8.01 | 7.41 | 7.14 | 7.68 | -0.257 | 0.078 | 0.001 |
| Poland | 7.48 | 7.43 | 7.54 | 7.56 | 7.51 | 7.62 | 6.55 | 6.32 | 6.78 | -0.458 | 0.061 | <0.001 |
| Portugal | 7.74 | 7.70 | 7.79 | 7.78 | 7.73 | 7.83 | 7.16 | 6.91 | 7.41 | -0.315 | 0.071 | <0.001 |
| Republic of Moldova | 8.25 | 8.20 | 8.30 | 8.26 | 8.21 | 8.31 | 8.12 | 7.93 | 8.31 | -0.037 | 0.063 | 0.554 |
| Romania | 8.32 | 8.28 | 8.37 | 8.39 | 8.34 | 8.44 | 7.88 | 7.73 | 8.03 | -0.266 | 0.048 | <0.001 |
| Russian Federation | 7.40 | 7.34 | 7.47 | 7.44 | 7.38 | 7.51 | 6.91 | 6.63 | 7.19 | -0.267 | 0.064 | <0.001 |
| Scotland | 7.63 | 7.57 | 7.69 | 7.72 | 7.66 | 7.78 | 6.79 | 6.55 | 7.02 | -0.415 | 0.063 | <0.001 |
| Serbia | 8.26 | 8.20 | 8.32 | 8.32 | 8.26 | 8.38 | 7.47 | 7.20 | 7.74 | -0.402 | 0.079 | <0.001 |
| Slovenia | 7.95 | 7.90 | 8.00 | 8.00 | 7.95 | 8.05 | 7.04 | 6.78 | 7.29 | -0.454 | 0.078 | <0.001 |
| Spain | 8.06 | 8.01 | 8.12 | 8.14 | 8.08 | 8.19 | 7.62 | 7.44 | 7.79 | -0.266 | 0.051 | <0.001 |
| Sweden | 7.45 | 7.39 | 7.51 | 7.52 | 7.45 | 7.58 | 6.20 | 5.86 | 6.54 | -0.590 | 0.083 | <0.001 |
| Switzerland | 7.67 | 7.62 | 7.71 | 7.72 | 7.68 | 7.77 | 6.43 | 6.15 | 6.70 | -0.680 | 0.073 | <0.001 |
| Turkey | 6.61 | 6.55 | 6.68 | 6.67 | 6.61 | 6.74 | 6.13 | 5.94 | 6.32 | -0.210 | 0.042 | <0.001 |
| Ukraine | 7.71 | 7.66 | 7.75 | 7.75 | 7.70 | 7.80 | 7.11 | 6.89 | 7.33 | -0.332 | 0.061 | <0.001 |
| Wales | 7.59 | 7.56 | 7.62 | 7.71 | 7.68 | 7.75 | 6.69 | 6.57 | 6.81 | -0.462 | 0.033 | <0.001 |

*Notes.* SMU = social media use; LL = confidence interval lower limit; UL = confidence interval upper limit; $\beta$ = STDY-standardized (i.e., *B*/standard deviation(Y)), controlled for gender, age, and socioeconomic status; *SE* = standard error; *p* = p-value.

3

**Table A3.11**

*Psychosomatic Complaints, by Problematic SMU and Country (n = 222,532 in 44 Countries)*

| | Means, total | | | Means, non-problematic | | | Means, problematic | | | Effect size mean differences | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | 95% LL | 95% UL | Mean | 95% LL | 95% UL | Mean | 95% LL | 95% UL | *β* | *SE* | *p* |
| Albania | 1.89 | 1.85 | 1.93 | 1.82 | 1.78 | 1.86 | 2.40 | 2.27 | 2.53 | 0.623 | 0.088 | <0.001 |
| Armenia | 1.86 | 1.84 | 1.88 | 1.83 | 1.81 | 1.85 | 2.31 | 2.19 | 2.42 | 0.634 | 0.082 | <0.001 |
| Austria | 1.99 | 1.97 | 2.02 | 1.96 | 1.94 | 1.99 | 2.65 | 2.50 | 2.79 | 0.806 | 0.081 | <0.001 |
| Azerbaijan | 1.67 | 1.65 | 1.70 | 1.60 | 1.57 | 1.63 | 2.35 | 2.26 | 2.44 | 0.924 | 0.074 | <0.001 |
| Belgium (Flanders) | 1.99 | 1.97 | 2.01 | 1.95 | 1.93 | 1.97 | 2.50 | 2.39 | 2.61 | 0.714 | 0.077 | <0.001 |
| Belgium (Wallonia) | 2.22 | 2.20 | 2.24 | 2.18 | 2.15 | 2.20 | 2.68 | 2.60 | 2.76 | 0.574 | 0.049 | <0.001 |
| Canada | 2.09 | 2.07 | 2.12 | 2.05 | 2.03 | 2.07 | 2.74 | 2.63 | 2.86 | 0.699 | 0.069 | <0.001 |
| Croatia | 1.89 | 1.87 | 1.92 | 1.83 | 1.80 | 1.85 | 2.46 | 2.38 | 2.55 | 0.714 | 0.055 | <0.001 |
| Czechia | 2.05 | 2.03 | 2.07 | 2.02 | 2.01 | 2.04 | 2.56 | 2.47 | 2.64 | 0.669 | 0.060 | <0.001 |
| Denmark | 1.97 | 1.95 | 2.00 | 1.95 | 1.92 | 1.98 | 2.52 | 2.34 | 2.69 | 0.688 | 0.112 | <0.001 |
| England | 2.18 | 2.15 | 2.21 | 2.13 | 2.09 | 2.16 | 2.77 | 2.63 | 2.91 | 0.666 | 0.089 | <0.001 |
| Estonia | 2.16 | 2.13 | 2.19 | 2.12 | 2.09 | 2.14 | 2.86 | 2.74 | 2.98 | 0.795 | 0.064 | <0.001 |
| Finland | 2.22 | 2.19 | 2.25 | 2.16 | 2.13 | 2.20 | 2.70 | 2.59 | 2.82 | 0.598 | 0.068 | <0.001 |
| France | 2.20 | 2.18 | 2.22 | 2.16 | 2.14 | 2.18 | 2.74 | 2.66 | 2.82 | 0.671 | 0.055 | <0.001 |
| Georgia | 2.06 | 2.03 | 2.09 | 2.04 | 2.02 | 2.07 | 2.42 | 2.27 | 2.58 | 0.408 | 0.090 | <0.001 |
| Germany | 2.03 | 2.01 | 2.05 | 2.00 | 1.98 | 2.03 | 2.52 | 2.39 | 2.65 | 0.713 | 0.094 | <0.001 |
| Greece | 2.16 | 2.13 | 2.18 | 2.09 | 2.06 | 2.12 | 2.78 | 2.69 | 2.87 | 0.713 | 0.058 | <0.001 |
| Hungary | 2.21 | 2.18 | 2.24 | 2.17 | 2.14 | 2.20 | 2.90 | 2.77 | 3.04 | 0.816 | 0.088 | <0.001 |
| Iceland | 2.20 | 2.18 | 2.22 | 2.17 | 2.15 | 2.20 | 2.69 | 2.57 | 2.82 | 0.564 | 0.065 | <0.001 |
| Ireland | 2.04 | 2.01 | 2.07 | 1.97 | 1.94 | 2.00 | 2.56 | 2.48 | 2.65 | 0.638 | 0.056 | <0.001 |
| Israel | 2.40 | 2.38 | 2.43 | 2.36 | 2.33 | 2.38 | 3.26 | 3.12 | 3.41 | 0.872 | 0.072 | <0.001 |
| Italy | 2.42 | 2.39 | 2.45 | 2.36 | 2.34 | 2.39 | 2.89 | 2.81 | 2.98 | 0.573 | 0.054 | <0.001 |
| Kazakhstan | 1.72 | 1.70 | 1.75 | 1.71 | 1.68 | 1.73 | 2.06 | 1.92 | 2.20 | 0.453 | 0.094 | <0.001 |
| Latvia | 2.14 | 2.11 | 2.16 | 2.10 | 2.08 | 2.13 | 2.75 | 2.61 | 2.89 | 0.663 | 0.078 | <0.001 |
| Lithuania | 1.99 | 1.96 | 2.01 | 1.94 | 1.91 | 1.97 | 2.49 | 2.38 | 2.61 | 0.630 | 0.058 | <0.001 |
| Luxembourg | 2.21 | 2.18 | 2.23 | 2.17 | 2.14 | 2.19 | 2.68 | 2.58 | 2.78 | 0.635 | 0.068 | <0.001 |
| Malta | 2.37 | 2.33 | 2.41 | 2.27 | 2.23 | 2.30 | 2.90 | 2.80 | 3.00 | 0.645 | 0.062 | <0.001 |
| Netherlands | 1.91 | 1.89 | 1.94 | 1.89 | 1.87 | 1.91 | 2.61 | 2.44 | 2.78 | 0.859 | 0.111 | <0.001 |
| North Macedonia | 1.78 | 1.75 | 1.81 | 1.72 | 1.69 | 1.75 | 2.36 | 2.26 | 2.46 | 0.763 | 0.062 | <0.001 |
| Norway | 1.92 | 1.90 | 1.95 | 1.90 | 1.87 | 1.93 | 2.15 | 2.04 | 2.26 | 0.309 | 0.079 | <0.001 |
| Poland | 2.14 | 2.11 | 2.16 | 2.09 | 2.06 | 2.11 | 2.73 | 2.64 | 2.82 | 0.710 | 0.060 | <0.001 |
| Portugal | 1.91 | 1.89 | 1.93 | 1.88 | 1.85 | 1.90 | 2.44 | 2.33 | 2.55 | 0.656 | 0.066 | <0.001 |
| Republic of Moldova | 2.01 | 1.98 | 2.03 | 1.98 | 1.96 | 2.01 | 2.27 | 2.17 | 2.36 | 0.322 | 0.068 | <0.001 |
| Romania | 2.12 | 2.09 | 2.14 | 2.04 | 2.02 | 2.07 | 2.62 | 2.54 | 2.69 | 0.603 | 0.046 | <0.001 |
| Russian Federation | 1.98 | 1.95 | 2.00 | 1.94 | 1.91 | 1.97 | 2.43 | 2.31 | 2.55 | 0.559 | 0.068 | <0.001 |
| Scotland | 2.06 | 2.03 | 2.08 | 2.00 | 1.97 | 2.02 | 2.64 | 2.54 | 2.74 | 0.670 | 0.064 | <0.001 |
| Serbia | 1.86 | 1.84 | 1.89 | 1.82 | 1.80 | 1.85 | 2.40 | 2.27 | 2.52 | 0.635 | 0.093 | <0.001 |
| Slovenia | 1.91 | 1.89 | 1.94 | 1.88 | 1.86 | 1.90 | 2.55 | 2.43 | 2.66 | 0.731 | 0.069 | <0.001 |
| Spain | 1.81 | 1.79 | 1.83 | 1.76 | 1.74 | 1.79 | 2.10 | 2.03 | 2.18 | 0.446 | 0.046 | <0.001 |
| Sweden | 2.32 | 2.29 | 2.35 | 2.28 | 2.26 | 2.31 | 2.98 | 2.84 | 3.12 | 0.718 | 0.086 | <0.001 |
| Switzerland | 2.08 | 2.06 | 2.10 | 2.05 | 2.03 | 2.07 | 2.74 | 2.64 | 2.84 | 0.885 | 0.064 | <0.001 |
| Turkey | 2.44 | 2.42 | 2.47 | 2.39 | 2.36 | 2.41 | 2.90 | 2.83 | 2.97 | 0.527 | 0.043 | <0.001 |
| Ukraine | 2.16 | 2.14 | 2.18 | 2.12 | 2.10 | 2.14 | 2.62 | 2.53 | 2.71 | 0.606 | 0.062 | <0.001 |
| Wales | 2.10 | 2.09 | 2.12 | 2.02 | 2.01 | 2.04 | 2.68 | 2.63 | 2.73 | 0.692 | 0.030 | <0.001 |

*Notes.* SMU = social media use; LL = confidence interval lower limit; UL = confidence interval upper limit; *β* = STDY-standardized (i.e., *B*/standard deviation(Y)), controlled for gender, age, and socioeconomic status; *SE* = standard error; *p* = p-value.

**Table A3.12**

*Intensity of Online Communication, by Problematic SMU and Country (n = 222,532 in 44 Countries)*

| | Means, total | | | Means, non-problematic | | | Means, problematic | | | Effect size mean differences | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | 95% LL | 95% UL | Mean | 95% LL | 95% UL | Mean | 95% LL | 95% UL | *β* | *SE* | *p* |
| Albania | 4.04 | 3.98 | 4.10 | 4.01 | 3.94 | 4.07 | 4.31 | 4.14 | 4.47 | 0.201 | 0.079 | 0.011 |
| Armenia | 3.58 | 3.53 | 3.62 | 3.56 | 3.52 | 3.61 | 3.79 | 3.61 | 3.96 | 0.163 | 0.072 | 0.023 |
| Austria | 3.87 | 3.83 | 3.90 | 3.84 | 3.81 | 3.88 | 4.37 | 4.25 | 4.49 | 0.470 | 0.059 | <0.001 |
| Azerbaijan | 2.79 | 2.74 | 2.84 | 2.84 | 2.79 | 2.89 | 2.33 | 2.16 | 2.49 | -0.273 | 0.086 | 0.001 |
| Belgium (Flanders) | 3.71 | 3.67 | 3.76 | 3.68 | 3.64 | 3.72 | 4.20 | 4.06 | 4.33 | 0.323 | 0.058 | <0.001 |
| Belgium (Wallonia) | 3.91 | 3.87 | 3.94 | 3.86 | 3.82 | 3.89 | 4.41 | 4.32 | 4.51 | 0.416 | 0.042 | <0.001 |
| Canada | 3.71 | 3.68 | 3.74 | 3.68 | 3.64 | 3.71 | 4.17 | 4.06 | 4.29 | 0.341 | 0.054 | <0.001 |
| Croatia | 3.73 | 3.69 | 3.77 | 3.69 | 3.65 | 3.73 | 4.11 | 4.00 | 4.22 | 0.282 | 0.051 | <0.001 |
| Czechia | 3.40 | 3.38 | 3.42 | 3.36 | 3.34 | 3.39 | 4.09 | 3.99 | 4.18 | 0.538 | 0.045 | <0.001 |
| Denmark | 3.86 | 3.82 | 3.89 | 3.84 | 3.80 | 3.88 | 4.17 | 3.98 | 4.37 | 0.252 | 0.097 | 0.009 |
| England | 3.76 | 3.72 | 3.80 | 3.71 | 3.67 | 3.76 | 4.29 | 4.14 | 4.44 | 0.440 | 0.072 | <0.001 |
| Estonia | 3.81 | 3.78 | 3.84 | 3.79 | 3.76 | 3.82 | 4.16 | 4.03 | 4.29 | 0.343 | 0.060 | <0.001 |
| Finland | 3.83 | 3.79 | 3.87 | 3.79 | 3.75 | 3.83 | 4.16 | 4.03 | 4.29 | 0.317 | 0.067 | <0.001 |
| France | 3.84 | 3.81 | 3.87 | 3.80 | 3.77 | 3.83 | 4.30 | 4.21 | 4.40 | 0.367 | 0.046 | <0.001 |
| Georgia | 3.64 | 3.60 | 3.67 | 3.63 | 3.59 | 3.67 | 3.75 | 3.56 | 3.94 | 0.082 | 0.083 | 0.328 |
| Germany | 3.62 | 3.58 | 3.66 | 3.60 | 3.56 | 3.63 | 4.05 | 3.89 | 4.21 | 0.392 | 0.078 | <0.001 |
| Greece | 3.73 | 3.69 | 3.77 | 3.68 | 3.64 | 3.72 | 4.19 | 4.08 | 4.30 | 0.327 | 0.049 | <0.001 |
| Hungary | 3.75 | 3.72 | 3.79 | 3.73 | 3.70 | 3.76 | 4.22 | 4.09 | 4.36 | 0.506 | 0.071 | <0.001 |
| Iceland | 3.79 | 3.76 | 3.81 | 3.77 | 3.74 | 3.80 | 4.16 | 4.03 | 4.29 | 0.266 | 0.063 | <0.001 |
| Ireland | 3.85 | 3.81 | 3.89 | 3.79 | 3.75 | 3.83 | 4.31 | 4.22 | 4.41 | 0.354 | 0.046 | <0.001 |
| Israel | 3.85 | 3.82 | 3.89 | 3.84 | 3.80 | 3.87 | 4.15 | 4.01 | 4.29 | 0.228 | 0.063 | <0.001 |
| Italy | 4.15 | 4.11 | 4.18 | 4.12 | 4.08 | 4.15 | 4.36 | 4.26 | 4.45 | 0.206 | 0.044 | <0.001 |
| Kazakhstan | 3.53 | 3.48 | 3.57 | 3.51 | 3.46 | 3.55 | 3.92 | 3.70 | 4.14 | 0.284 | 0.078 | <0.001 |
| Latvia | 3.46 | 3.43 | 3.50 | 3.44 | 3.40 | 3.48 | 3.92 | 3.75 | 4.08 | 0.382 | 0.069 | <0.001 |
| Lithuania | 3.93 | 3.89 | 3.96 | 3.91 | 3.87 | 3.94 | 4.16 | 4.03 | 4.30 | 0.212 | 0.058 | <0.001 |
| Luxembourg | 3.78 | 3.75 | 3.82 | 3.75 | 3.71 | 3.79 | 4.25 | 4.13 | 4.36 | 0.397 | 0.053 | <0.001 |
| Malta | 4.02 | 3.97 | 4.06 | 3.97 | 3.92 | 4.02 | 4.27 | 4.17 | 4.38 | 0.254 | 0.060 | <0.001 |
| Netherlands | 3.71 | 3.68 | 3.74 | 3.69 | 3.66 | 3.73 | 4.18 | 4.00 | 4.36 | 0.339 | 0.079 | <0.001 |
| North Macedonia | 4.10 | 4.07 | 4.13 | 4.07 | 4.04 | 4.11 | 4.37 | 4.27 | 4.46 | 0.220 | 0.052 | <0.001 |
| Norway | 3.86 | 3.81 | 3.90 | 3.84 | 3.79 | 3.88 | 4.06 | 3.91 | 4.20 | 0.166 | 0.060 | 0.005 |
| Poland | 3.98 | 3.95 | 4.01 | 3.96 | 3.92 | 3.99 | 4.31 | 4.21 | 4.41 | 0.264 | 0.047 | <0.001 |
| Portugal | 3.93 | 3.90 | 3.96 | 3.91 | 3.88 | 3.94 | 4.28 | 4.16 | 4.41 | 0.280 | 0.054 | <0.001 |
| Republic of Moldova | 3.85 | 3.81 | 3.88 | 3.81 | 3.77 | 3.85 | 4.28 | 4.16 | 4.40 | 0.343 | 0.049 | <0.001 |
| Romania | 4.05 | 4.02 | 4.09 | 4.01 | 3.98 | 4.05 | 4.31 | 4.22 | 4.40 | 0.234 | 0.046 | <0.001 |
| Russian Federation | 3.78 | 3.74 | 3.82 | 3.77 | 3.73 | 3.81 | 3.92 | 3.79 | 4.05 | 0.115 | 0.059 | 0.051 |
| Scotland | 3.94 | 3.90 | 3.97 | 3.89 | 3.85 | 3.92 | 4.45 | 4.35 | 4.54 | 0.469 | 0.046 | <0.001 |
| Serbia | 4.00 | 3.96 | 4.04 | 3.97 | 3.93 | 4.01 | 4.44 | 4.30 | 4.58 | 0.301 | 0.065 | <0.001 |
| Slovenia | 3.58 | 3.55 | 3.62 | 3.55 | 3.51 | 3.59 | 4.12 | 3.98 | 4.26 | 0.352 | 0.056 | <0.001 |
| Spain | 3.78 | 3.74 | 3.82 | 3.73 | 3.69 | 3.77 | 4.09 | 4.00 | 4.19 | 0.256 | 0.041 | <0.001 |
| Sweden | 3.98 | 3.94 | 4.02 | 3.95 | 3.92 | 3.99 | 4.44 | 4.31 | 4.58 | 0.341 | 0.062 | <0.001 |
| Switzerland | 3.52 | 3.50 | 3.55 | 3.49 | 3.47 | 3.52 | 4.20 | 4.09 | 4.31 | 0.635 | 0.052 | <0.001 |
| Turkey | 3.63 | 3.60 | 3.67 | 3.59 | 3.55 | 3.63 | 4.01 | 3.91 | 4.12 | 0.279 | 0.045 | <0.001 |
| Ukraine | 3.62 | 3.59 | 3.65 | 3.60 | 3.56 | 3.63 | 3.91 | 3.78 | 4.04 | 0.240 | 0.054 | <0.001 |
| Wales | 3.83 | 3.81 | 3.85 | 3.77 | 3.75 | 3.79 | 4.20 | 4.15 | 4.25 | 0.321 | 0.027 | <0.001 |

*Notes.* SMU = social media use; LL = confidence interval lower limit; UL = confidence interval upper limit; *β* = STDY-standardized (i.e., *B*/standard deviation(Y)), controlled for gender, age, and socioeconomic status; *SE* = standard error; *p* = p-value.

**Table A3.13**

*Summary of Sensitivity Analysis*

| | Cut-off 6-9 | | | Cut-off 5-9 | | | | Cut-off 7-9 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Countries[1]** | **$\beta$ average[2]** | **$\beta$ pooled[3]** | **Countries[1]** | **$\beta$ average[2]** | **$\beta$ pooled[3]** | **$r^4$** | **Countries[1]** | **$\beta$ average[2]** | **$\beta$ pooled[3]** | **$r^5$** |
| Problematic SMU and life satisfaction | 40 | -0.397 | -0.395 | 42 | -0.371 | -0.372 | 0.953 | 40 | -0.417 | -0.408 | 0.934 |
| Problematic SMU and psychosomatic complaints | 44 | 0.654 | 0.648 | 44 | 0.620 | 0.609 | 0.938 | 43 | 0.682 | 0.670 | 0.929 |
| Problematic SMU and intensity of online communication | 41 | 0.301 | 0.313 | 42 | 0.285 | 0.309 | 0.948 | 39 | 0.300 | 0.294 | 0.940 |

*Notes*. SMU = social media use; $\beta$ = STDY-effect size (i.e., *B*/standard deviation(Y)), controlled for gender, age, and socioeconomic status.
[1] Number of countries where a significant association was observed in the same direction as in the pooled sample.
[2] Average magnitude of the association computed from the effect sizes of 44 countries.
[3] Magnitude of the associated computed from the pooled sample.
[4] Correlation between the effect sizes based on a 5-9 cut-off and the effect sizes based on a 6-9 cut-off ($n$ = 44 countries).
[5] Correlation between the effect sizes based on a 7-9 cut-off and the effect sizes based on a 6-9 cut-off ($n$ = 44 countries).

3

# CHAPTER 4

## ADOLESCENTS' INTENSE AND PROBLEMATIC SOCIAL MEDIA USE AND THEIR WELLBEING IN 29 COUNTRIES

Maartje Boer, Regina J. J. M. van den Eijnden, Meyran Boniel-Nissim, Suzy-Lai Wong, Jo Inchley, Petr Badura, Wendy M. Craig, Inese Gobina, Dorota Kleszczewska, Helena J. Klanšček, and Gonneke W. J. M. Stevens

**Author Contributions**

MB, GS, and RvdE conceived of the study. MB conducted the literature review, data analyses, and drafted the initial and revised manuscript. GS and RvdE advised during all stages of preparing and revising the manuscript. JI was the international coordinator of the HBSC study. All authors critically reviewed the initial and reviewed manuscript, and approved of the final manuscript.

**Publication**

Boer, M., Van den Eijnden, R. J. J. M., Boniel-Nissim, M., Wong, S. L., Inchley, J. C., Badura, P., Craig, W. M., Gobina, I., Kleszczewska, D., Klanšček, H. J., & Stevens, G. W. J. M. (2020). Adolescents' intense and problematic social media use and their well-being in 29 countries. *Journal of Adolescent Health*, *66*(6), S89-S99. https://doi.org/10.1016/j.jadohealth.2020.02.014

# Abstract

This study examined (1) whether intense and problematic social media use (SMU) were independently associated with adolescent wellbeing, (2) whether these associations varied by the country-level prevalence of intense and problematic SMU, and (3) whether differences in the country-level prevalence of intense and problematic SMU were related to differences in mobile internet access. Individual-level data came from 154,981 adolescents ($M_{age}$ = 13.5) from 29 countries that participated in the 2017/2018 Health Behaviour in School-aged Children survey. Mental (life satisfaction, psychological complaints), school (school satisfaction, perceived school pressure), and social (family support, friend support) wellbeing were assessed. Country-level data came from aggregated individual-level data and OECD data on internet access. Multilevel analyses indicated that in countries with a lower prevalence of intense SMU, intense users reported lower levels of life satisfaction and family support, and more psychological complaints than non-intense users. In contrast, in countries with a higher prevalence of intense SMU, intense users reported higher levels of family support and life satisfaction than non-intense users, and similar levels of psychological complaints. In all countries, intense users reported more friend support than non-intense users. Consistent across countries, problematic users reported lower wellbeing on all domains than non-problematic users. Observed differences in country-level prevalence rates of intense and problematic SMU could not be explained by mobile internet access. Adolescents reporting problematic SMU are particularly at risk of lower wellbeing. In many countries, intense SMU may be a normative adolescent behavior that contributes positively to specific domains of their wellbeing.


*Keywords:* Social media use, problematic social media use, wellbeing, adolescents, cross-national research, HBSC.

# Adolescents' Intense and Problematic Social Media Use and Their Wellbeing in 29 Countries

Social media use (SMU) has become increasingly embedded in adolescents' daily lives in recent years, leading to concerns about its potential impact (Primack & Escobar-Viera, 2017; Underwood & Ehrenreich, 2017). In the United States, the percentage of adolescents that reports being online almost constantly has increased from 25% to 45% between 2015 and 2018 (Anderson & Jiang, 2018). In addition, two large-scale studies among European adolescents, conducted in 2014 and 2015, showed that the prevalence of addiction-like problematic SMU was 4.5% (Bányai et al., 2017) and 9.1% (Mérelle et al., 2017). Other than adolescents who merely show *intense SMU* by spending a lot of time on SMU, adolescents with *problematic SMU* typically have a diminished ability to regulate their SMU impulses, feel discomfort such as stress or anxiety when SMU is restricted, and have SMU on top of their mind constantly (Griffiths et al., 2014). Research suggests that intense SMU is linked to lower mental (Kelly et al., 2018; Primack & Escobar-Viera, 2017; Twenge, Joiner, et al., 2018), school (Al-Menayes, 2015b), and social wellbeing (Underwood & Ehrenreich, 2017) of adolescents. Moreover, problematic SMU is also associated with lower adolescent wellbeing (Marino et al., 2018b). However, important gaps in knowledge remain, three of which we address in this study.

First, intense and problematic SMU are distinct concepts, yet correlated (Boer, Stevens, et al., 2020; Van den Eijnden et al., 2016, 2018), but studies typically have not examined their associations with wellbeing simultaneously in one model. Therefore, it remains unclear whether intense and problematic SMU are as strongly associated with lower adolescent wellbeing. Second, existing research on intense and problematic SMU and their outcomes has typically used single-country data. Hence, it is not clear whether and to what extent the associations with wellbeing apply cross-nationally. Third, little is known about the extent to which adolescents' intense and problematic SMU differs across countries. The present study addresses these gaps by investigating independent associations of intense and problematic SMU with wellbeing across 29 countries.

Several mechanisms have been proposed for the negative associations of intense and problematic SMU with wellbeing. *Intense users* may be excessively exposed to unrealistic portrayals of others, which, in turn, may elicit upward social comparisons and decrease their mental wellbeing (Kelly et al., 2018; Pera, 2018). In addition, they may fall behind with their schoolwork due to their intensive SMU, which could induce lower school wellbeing (Al-Menayes, 2015b; Salmela-Aro et al., 2017). Moreover, intense users may spend less offline time with friends or family because of their intensive SMU, which may have a negative impact on their social wellbeing (Underwood & Ehrenreich, 2017; Wallsten, 2013). However, there are also reasons why intense SMU may not be, or only be weakly associated with low wellbeing. Intense SMU may be a common behavior among adolescents (Anderson & Jiang, 2018; Vannucci & McCauley Ohannessian, 2019), as social media often play an important role in their everyday social lives (Boyd, 2014). Furthermore, although intense SMU indicates adolescents' time spent on SMU, it does not indicate their ability to control their SMU. Consequently, detrimental consequences of intense SMU may be limited.

In contrast, *problematic users* typically feel bad when SMU is restricted (Griffiths et al., 2014), which conceivably harms their mental wellbeing. Also, the loss of control over and preoccupation with social media may impair their ability to regulate schoolwork responsibilities (Salmela-Aro et al., 2017) and may diminish their interest in offline social activities with others (Andreassen, 2015). As a result, problematic users may displace schoolwork and offline quality time with friends and family with SMU, which could affect their school and social wellbeing negatively. It, therefore, seems plausible that addiction-like problematic SMU interferes more strongly with wellbeing than intense SMU, yet this suggestion has rarely been investigated. The few studies that have examined adolescents' intense and problematic SMU simultaneously showed that problematic SMU, but not intense SMU, was associated with lower *mental* wellbeing (Boer, Stevens, et al., 2020; Shensa et al., 2017; Van den Eijnden et al., 2018). Thus, previously found negative relationships between SMU intensity and wellbeing may have resulted from a confounding effect of problematic SMU.

Furthermore, the associations of intense and problematic SMU with wellbeing may depend on the national context. Normalization theory, which mainly has been used to explain differences in substance use between varying contexts (Haskuka et al., 2018; Sznitman et al., 2015), suggests that once risk behaviors are socially and culturally accepted by the majority of the population and have become an unremarkable feature of life (Pennay &

Measham, 2016), these behaviors may become normalized and consequently represent mainstream adolescents without problematic profiles (Sznitman et al., 2015). Hence, engaging in these behaviors may not necessarily indicate lower wellbeing. Similarly, when intense and problematic SMU are widespread in society, these behaviors may become normalized. Consequently, when the country-level prevalence of intense or problematic SMU is high, the proposed negative associations with wellbeing may be low or even absent. In addition, differences in the country-level prevalence of intense and problematic SMU may be related to cross-national differences in the accessibility of mobile internet, such as the countries' average costs and speed of mobile internet, as adolescents typically use social media through mobile internet devices, such as smartphones (Eurostat, 2015).



### Current Study

Using data from 29 countries participating in the Health Behaviour in School-aged Children (HBSC) survey (2017/2018), the present study investigated whether adolescents' intense and problematic SMU were associated with their wellbeing, and whether these associations varied across countries. We expected that, compared with intense SMU, problematic SMU would be more strongly associated with lower mental, school, and social wellbeing. We also expected that associations between both types of SMU and low wellbeing would be weaker in countries with a higher prevalence of intense and problematic SMU. The study also investigated whether cross-national differences in the prevalence of intense and problematic SMU were related to country-level mobile internet access. We expected that countries with more favourable mobile internet access would report a higher prevalence of adolescent intense and problematic SMU.

## Methods

### Sample

The HBSC survey is a cross-national study that has been conducted every four years since 1983 to monitor the health behavior of 11-, 13-, and 15-year-olds across Europe, North America, and the Middle East. The present study used the 2017/2018 data, which included nationally representative data of adolescents from 47 countries/regions. Countries were excluded from the present study when individual-level data on SMU ($n_{\text{countries}}$ = 3) or country-level data on mobile internet accessibility were unavailable ($n_{\text{countries}}$ = 13), or when data were not submitted by the time of current analyses ($n_{\text{countries}}$ = 2). Adolescents who responded that the SMU questions did not apply to them were also excluded ($n_{\text{individuals}}$ = 6,174). The analysis sample consisted of 154,981 adolescents within 29 countries/regions (51% girls, $M_{\text{age}}$ = 13.54; $SD_{\text{age}}$ = 1.61). Sampling methods (schools or classes as primary sampling units), data collection procedures, and questionnaires were standardized and strictly followed the HBSC international research protocol (Inchley et al., 2018). Before the survey assessments, in each country, researchers translated the English survey questions into the respective national language. Subsequently, different researchers back-translated the survey questions to English without prior knowledge of the original English survey questions. Next, language experts within the HBSC network compared the original and back-translated English survey questions. Detected inconsistencies were corrected in the national language surveys to ensure comparability of findings across different languages and cultural settings (Inchley et al., 2018). Institutional ethical consent was sought in each participating country. Participation was voluntary and anonymous, and consent was obtained from adolescents, parents, and schools.

## Individual-Level Measures

### *Intense SMU*

Using four items adapted from the EU Kids Online Survey (Mascheroni & Ólafsson, 2014), respondents were asked how often they have online contact through social media with close friends, friends from a larger friend group, friends that they met through the internet, and other people (e.g., parents, siblings, classmates, teachers), with responses ranging from 1 *never/almost never* to 5 *almost all the time throughout the day,* and a *don't know/doesn't apply* option. Respondents who answered *almost all the time throughout the day* on at least one item were classified as 1 *intense user,* and the remainder as 0 *non-intense user*. The items of the scale were not expected to have high intercorrelations (e.g., adolescents with intense contact with close friends were not necessarily expected to have intense contact with friends met through internet). Therefore, the internal consistency of the items was not assessed (Bollen & Lennox, 1991).

### *Problematic SMU*

Using the 9-item Social Media Disorder-Scale (Van den Eijnden et al., 2016) respondents indicated whether they, in the past year, regularly could not think of anything else but social media (preoccupation), regularly felt dissatisfied because they wanted to spend more time on social media (tolerance), often felt bad when they could not use social media (withdrawal), failed to spend less time on social media (persistence), regularly neglected other activities because of social media (displacement), regularly had arguments with others because of their SMU (problem), regularly lied to parents or friends about their time spent on social media (deception), often used social media to escape from negative feelings (escape), and had serious conflicts with parents or siblings because of their SMU (conflict). Response options were 1 *yes* and 0 *no*. Respondents who answered positively to at least six items were classified as 1 *problematic user*, and the remainder as 0 *non-problematic user* (Boer, Stevens, Finkenauer, Koning, et al., 2021). Given the dichotomous nature of the items, internal consistency was calculated using the tetrachoric correlation matrix (Gadermann et al., 2012), yielding an alpha of 0.89.

### *Mental Wellbeing*

Two measures assessed mental wellbeing. Respondents rated their *life satisfaction* using Cantril's ladder (Cantril, 1965), ranging from 0 *worst possible life* to 10 *best possible life*. The single-item nature of the measure did not allow for assessing internal consistency. However, the measure has been found to provide good test-retest reliability among adolescents (Levin & Currie, 2014). A 4-item subscale from the HBSC Symptom Checklist assessed *psychological complaints* (Gariepy et al., 2016). Respondents were asked how often in the last six months they experienced feeling low, irritable, nervous, and had difficulties falling asleep. Responses ranged from 1 *about every day* to 5 *rarely or never*. Means were computed after items were rescaled. Hence, higher mean scores indicated more psychological complaints. The internal consistency of the items was adequate (Cronbach's alpha = 0.75).

### *School Wellbeing*

Two measures were used. Respondents indicated their *school satisfaction* ranging from 1 *I like it a lot* to 4 *I don't like it at all* (Inchley et al., 2016). Scores were rescaled such that high values indicated high school satisfaction. Respondents also indicated their *perceived school pressure* by rating how pressured they felt by schoolwork, ranging from 1 *not at all* to 4 *a lot* (Inchley et al., 2016). Internal consistency was not calculated given the single-item nature of the measures. Yet, these measures have been used for many years within research using HBSC data (Inchley et al., 2016; Klinger et al., 2015; Torsheim & Wold, 2001).

### *Social Wellbeing*

Two 4-item subscales of the Multidimensional Scale of Perceived Social Support (MSPSS) (Zimet et al., 1988) were used to assess social wellbeing. The first subscale includes *family support*. This subscale assessed, for example, whether they can talk about problems with their family, with responses ranging from 1 *very strongly disagree* to 7 *very strongly agree*. The second subscale includes *friend support* that assessed, for example, whether they can count on friends when things go wrong. For both subscales, we calculated adolescents' mean scores. The internal consistency of both subscales was very good (Cronbach's alpha = 0.94 and 0.93).

### *Controls*

The analyses were controlled for *gender*, *age* and *family affluence*. Family affluence was indicated by six items. Respondents reported the households' number of cars (0 *none*, 1 *one*, 2 *two or more*), computers (0 *none*, 1 *one*, 2 *two*, 3 *more than two*), and bathrooms (0 *none*, 1 *one*, 2 *two*, 3 *more than two*), whether they had their own bedroom (0 *no*, 1 *yes*), whether they had a dishwasher (0 *no*, 1 *yes*), and the number of holidays spent abroad in the past year (0 *not at all*, 1 *once*, 2 *twice*, 3 *more than twice*). Sum-scores were transformed into proportional ranks that indicate adolescents' relative family affluence in their residential country (varying from 0 *lowest* to 1 *highest*) (Elgar et al., 2017).

## Country-Level Measures

### *Country Prevalence Intense SMU*

The prevalence of intense SMU was calculated as each country's proportion of respondents that were classified as intense users.

### *Country Prevalence Problematic SMU*

The prevalence of problematic SMU was calculated as each country's proportion of respondents that were classified as problematic users.



### *Mobile Internet Access*

Two measures obtained from OECD-data were used (OECD, 2019). *Costs of mobile broadband* was assessed using the countries' average price of a basket of mobile monthly usage of 300 calls and 1 gigabyte internet in 2017. To facilitate international comparisons, prices were standardized by taking into account different price levels between countries (OECD, 2019). Countries' *internet speed* was indicated by download speed in megabits per second in 2017.

## Analysis

### *Missing Data*

In the analysis sample, 22.4% of respondents had missing data on at least one individual-level variable, with problematic SMU having the most missing data (9.8% of the analysis sample). To retain all respondents, missing data were imputed using multiple imputation with Mplus 8.3. Five imputations were generated using the default unrestricted 'covariance' method (Asparouhov & Muthén, 2010b). Missing data were imputed based on available data on the individual-level study variables as well as dummy variables indicating countries to account for the nested structure of the data (Reiter et al., 2006). Iceland did not have data on internet speed, and Lithuania did not have data on mobile broadband costs. To retain these countries, these two missing values were imputed based on available information on countries' Gross Domestic Product (GDP), number of mobile broadband subscriptions, average data usage per mobile broadband subscription (OECD, 2019), and countries' intense and problematic SMU prevalence.

### *Modelling*

Two-level regression analyses were conducted on the imputed datasets using Mplus 8.3, with individual-level measures at the first level and country-level measures at the second level. Although the data consist of a three-level structure, where individuals were nested in schools and countries, applying three-level analyses was not feasible because then the number of parameters would exceed the number of country-clusters, which does not provide model identification. In addition, to retain fewer parameters than country-clusters, associations with all six wellbeing outcomes were examined in separate models. Models were estimated using Maximum Likelihood estimation with Robust standard errors to account for the skewed distribution of the wellbeing outcomes.

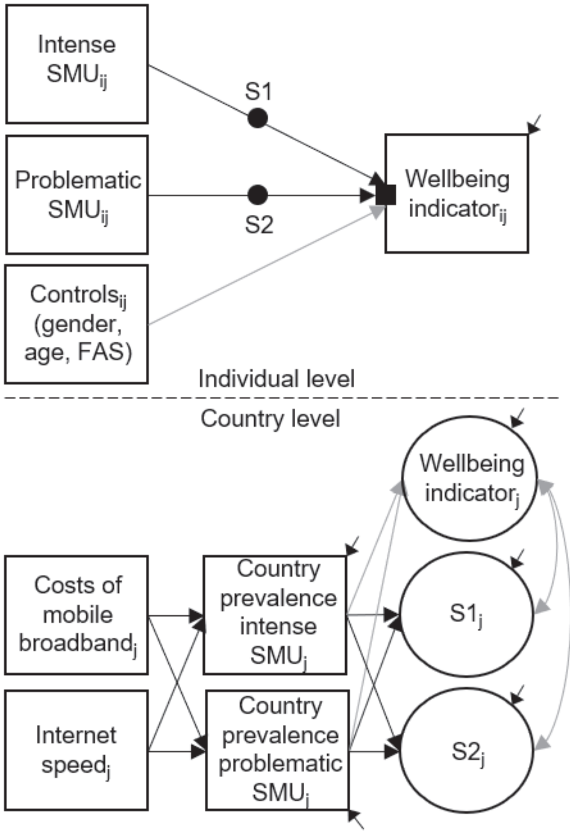
Figure 4.1 illustrates our analytical model, which was examined using a stepwise procedure. In our first model (denoted as $M1_a$), on the individual-level, we examined associations between intense and problematic SMU and life satisfaction (while controlling for gender, age, and family affluence) without any country variation. On the country-level, we tested associations between mobile internet access and the country-level prevalence of intense and problematic SMU ($M1_a$). We extended this model with a random slope (S1) for intense SMU, which means that its association with life satisfaction was allowed to vary across countries ($M1_b$). Subsequently, we added a random slope (S2) for problematic SMU ($M1_c$). Next, we added two cross-level interactions that examined whether the association between intense SMU and life satisfaction varied by the country-level prevalence of intense SMU ($M1_d$) and problematic SMU ($M1_e$). Finally, we added two additional cross-level interactions that examined whether the association between problematic SMU and life satisfaction varied by the country-level prevalence of intense SMU ($M1_f$) and problematic SMU ($M1_g$). These steps were repeated for the other five wellbeing outcomes ($M2_{a-g}$ to $M6_{a-g}$).

### *Interpretations*

After the stepwise analyses were conducted, for each wellbeing outcome, we selected the model with the best model fit for further interpretation. As a result, random slopes and cross-level interactions were only interpreted when they improved model fit. Model fit was evaluated using the Bayesian

**Figure 4.1**

*Analytical Model*




*Notes.* SMU = social media use; FAS = family affluence; Subscripts *i* and *j* denote individuals (i) in countries (j); Black circles denote random slopes (S1 and S2); Black square denotes random intercept; White squares denote observed variables; White circles denote latent variables; Grey arrows denote estimates that were added for control purposes. The analytical model was applied to all six wellbeing measures.

Information Criterion (BIC) and Akaike Information Criterion (AIC), where lower values indicated better model fit (Burnham & Anderson, 2004). Further, associations were interpreted using their 95% prediction intervals (PIs) (Hox, 2010d), which indicate the estimated range of the associations across countries. Cross-level interactions were evaluated on their explained variance (Hox, 2010c). All continuous study variables were mean-centered to facilitate interpretation of the cross-level interactions (Hox, 2010c).

# Results

## Bivariate Correlations

Table 4.1 shows the descriptive statistics and correlations of the individual-level and country-level variables. On the individual-level, intense and problematic SMU were correlated, with small to moderate effect size ($r$ = 0.269). Intense SMU was associated with lower mental and school wellbeing, although effect sizes were small ($r$ < 0.119). Intense SMU was associated with higher levels of friend support, with a small effect size ($r$ = 0.117), but not with family support. Problematic SMU was correlated with lower mental, school, and social wellbeing, with effect sizes ranging from small (friend support: $r$ = -0.068) to moderate (psychological complaints: $r$ = 0.290). At the country level, a higher prevalence of intense SMU was strongly associated with a higher prevalence of problematic SMU ($r$ = 0.476). The cost of mobile broadband and internet speed were not correlated with countries' intense and problematic SMU prevalence.

## Model Selection

Table 4.2 shows the model fits of models (M) following a stepwise procedure. Results showed that in all models, adding random slopes for intense and problematic SMU improved model fit in terms of AIC and/or BIC ($M1\text{-}6_b$ and $M1\text{-}6_c$), which suggests that associations between both types of SMU and all six wellbeing indicators varied across countries. For life satisfaction, only the cross-level interaction between intense SMU and country-level intense SMU prevalence further improved model fit ($M_{1d}$). The same applied to psychological complaints, although the respective cross-level interaction improved AIC, but not BIC ($M_{2d}$). For both school wellbeing outcomes, models without any cross-level interaction showed the best model fit ($M_{3c}$ and $M_{4c}$). For both social wellbeing outcomes, the model with all four cross-level interactions showed the best model fit in terms of AIC, but not BIC ($M_{5g}$ and $M_{6g}$). For each wellbeing outcome, we selected the models with the best model fit for further interpretation. When AIC and BIC were inconclusive, we selected the models with the lowest AIC, because these models included cross-level interactions that reduced the country-variance in the investigated associations, suggesting that the respective cross-level interactions were present.

**Table 4.1**

*Descriptive Statistics and Correlations*

| | *Individual-level (n = 154,981)* | **Mean / Proportion** | **SD** | **Min.** | **Max.** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Intense SMU | 0.340 | | | | 1 | | | | | | | |
| 2 | Problematic SMU | 0.074 | | | | 0.269*** | 1 | | | | | | |
| | *Mental wellbeing* | | | | | | | | | | | | |
| 3 | Life satisfaction | 7.639 | 1.846 | 0 | 10 | -0.042*** | -0.203*** | 1 | | | | | |
| 4 | Psychological complaints | 2.351 | 1.024 | 1.000 | 5.000 | 0.119*** | 0.290*** | -0.463*** | 1 | | | | |
| | *School wellbeing* | | | | | | | | | | | | |
| 5 | School satisfaction | 2.866 | 0.872 | 1 | 4 | -0.082*** | -0.198*** | 0.295*** | -0.273*** | 1 | | | |
| 6 | Perceived school pressure | 2.368 | 0.922 | 1 | 4 | 0.101*** | 0.187*** | -0.236*** | 0.333*** | -0.263*** | 1 | | |
| | *Social wellbeing* | | | | | | | | | | | | |
| 7 | Family support | 5.623 | 1.659 | 1.000 | 7.000 | -0.010 | -0.171*** | 0.325*** | -0.246*** | 0.180*** | -0.135*** | 1 | |
| 8 | Friends support | 5.305 | 1.766 | 1.000 | 7.000 | 0.117*** | -0.068*** | 0.174*** | -0.123*** | 0.141*** | -0.075*** | 0.443*** | 1 |
| | *Controls* | | | | | | | | | | | | |
| 9 | Female | 0.510 | | | | 0.107*** | 0.077*** | -0.119*** | 0.227*** | 0.064*** | 0.124*** | -0.047*** | 0.135*** |
| 10 | Family affluence | 0.502 | 0.285 | 0.000 | 0.998 | 0.033*** | -0.015* | 0.132*** | -0.038*** | 0.025*** | 0.008 | 0.066*** | 0.060*** |
| 11 | Age | 13.541 | 1.645 | 10.000 | 16.500 | 0.156*** | 0.094*** | -0.188*** | 0.147*** | -0.187*** | 0.213*** | -0.123*** | -0.008 |
| | *Country-level (n = 29)* | **Mean / Proportion** | **SD** | **Min.** | **Max.** | **12** | **13** | **14** | **15** | | | | |
| 12 | Intense SMU prevalence | 0.346 | 0.072 | 0.174 | 0.499 | 1 | | | | | | | |
| 13 | Problematic SMU prevalence | 0.073 | 0.027 | 0.031 | 0.142 | 0.476*** | 1 | | | | | | |
| 14 | Costs mobile broadband | 24.341 | 14.792 | 9.849 | 72.506 | -0.024 | 0.139 | 1 | | | | | |
| 15 | Internet speed | 15.725 | 3.718 | 7.900 | 23.500 | -0.237 | -0.181 | -0.255 | 1 | | | | |

*Notes.* SMU = social media use; SD = standard deviation; Min. = minimum; Max. = maximum; Individual-level correlations were computed with a country cluster correction.
* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

**Table 4.2**

*Model Comparisons*

| Model | a | b | c | d | e | f | g |
|---|---|---|---|---|---|---|---|
| | intense + problematic SMU fixed | a + random slope intense SMU | b + random slope problematic SMU | c + intense SMU * country prevalence intense SMU | d + intense SMU * country prevalence problematic SMU | e + problematic SMU * country prevalence intense SMU | f + problematic SMU * country prevalence problematic SMU |
| **Free parameters** | **18** | **20** | **22** | **23** | **24** | **25** | **26** |
| **Mental wellbeing** | | | | | | | |
| *M1. Life satisfaction* | | | | | | | |
| AIC | 616143.1 | 616075.3 | 616026.6 | **616002.8** | 616004.8 | 616005.3 | 616004.8 |
| BIC | 616322.2 | 616274.3 | 616245.6 | **616231.7** | 616243.6 | 616254.1 | 616263.6 |
| $u1_j$ | | 0.011 | 0.010 | 0.002 | 0.002 | 0.002 | 0.002 |
| $u2_j$ | | | 0.033** | 0.034** | 0.034** | 0.031** | 0.028** |
| *M2. Psychological complaints* | | | | | | | |
| AIC | 430895.9 | 430807.2 | 430730.0 | **430723.3** | 430723.9 | 430724.2 | 430724.2 |
| BIC | 431075.0 | 431006.3 | **430948.9** | 430952.2 | 430962.7 | 430973.0 | 430983.0 |
| $u1_j$ | | 0.005** | 0.005** | 0.003** | 0.003** | 0.003** | 0.003** |
| $u2_j$ | | | 0.013* | 0.013* | 0.013* | 0.012* | 0.011* |
| **School wellbeing** | | | | | | | |
| *M3. School satisfaction* | | | | | | | |
| AIC | 383871.5 | 383805.0 | **383745.5** | 383747.5 | 383747.2 | 383748.9 | 383750.8 |
| BIC | 384050.7 | 384004.0 | **383964.4** | 383976.4 | 383986.0 | 383997.7 | 384009.5 |
| $u1_j$ | | 0.002** | 0.002** | 0.002** | 0.002** | 0.002** | 0.002** |
| $u2_j$ | | | 0.007** | 0.007** | 0.007** | 0.007** | 0.007** |
| *M4. Perceived school pressure* | | | | | | | |
| AIC | 399668.6 | 399615.8 | **399546.0** | 399548.0 | 399549.6 | 399547.8 | 399549.3 |
| BIC | 399847.7 | 399814.9 | **399764.9** | 399776.8 | 399788.4 | 399796.6 | 399808.0 |
| $u1_j$ | | 0.002* | 0.002* | 0.002* | 0.002** | 0.002** | 0.002** |
| $u2_j$ | | | 0.012 | 0.012 | 0.012 | 0.010 | 0.010 |
| **Social wellbeing** | | | | | | | |
| *M5. Family support* | | | | | | | |
| AIC | 597242.9 | 597185.1 | 597172.6 | 597159.2 | 597158.8 | 597160.7 | **597158.6** |
| BIC | 597422.1 | **597384.1** | 597391.5 | 597388.1 | 597397.6 | 597409.5 | 597417.4 |
| $u1_j$ | | 0.009** | 0.009** | 0.004* | 0.003* | 0.003* | 0.003* |
| $u2_j$ | | | 0.012* | 0.012* | 0.012* | 0.012* | 0.009* |
| *M6. Friend support* | | | | | | | |
| AIC | 597587.5 | 597504.2 | 597495.2 | 597485.3 | 597484.8 | 597486.7 | **597480.0** |
| BIC | 597766.6 | **597703.2** | 597714.1 | 597714.1 | 597723.6 | 597735.5 | 597738.8 |
| $u1_j$ | | 0.012** | 0.012** | 0.007* | 0.006 | 0.006 | 0.006 |
| $u2_j$ | | | 0.009 | 0.009 | 0.009 | 0.009 | 0.006 |

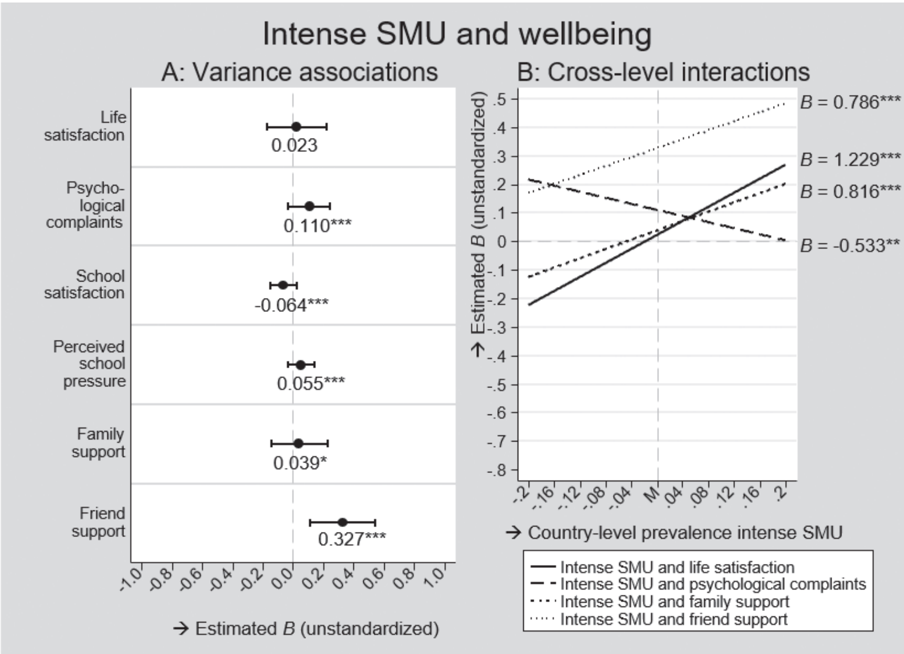
*Notes.* SMU = social media use; $u1_j$ = slope variance intense SMU; $u2_j$ = slope variance problematic SMU. Boldface AIC and BIC denote the lowest row values; Dark grey cells denote the models that were selected as final models for model interpretation.
* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

## Intense Social Media Use and Wellbeing

Figure 4.2 illustrates the associations between intense SMU and wellbeing outcomes according to the models with the best model fit. Estimates and further details of these models can be found in the Appendix (Table A4.1).

**Figure 4.2**

*Associations Between Intense SMU and Wellbeing*




*Notes.* SMU = social media use; B = unstandardized coefficient; M = mean.
Left (A): dots denote average estimated associations between intense SMU and the wellbeing outcomes, horizontal lines through the dots denote their 95% prediction interval.
Right (B): diagonal lines represent the estimated associations of intense SMU and the wellbeing outcomes by the country-level prevalence of intense SMU. Cross-level interactions were reported when they improved model fit and when they were significant at $p < 0.05$. All estimates were derived from multilevel regression models (Appendix, Table A4.1).
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

### *Mental Wellbeing*

Figure 4.2A shows that, on average, intense SMU and life satisfaction were not related ($B = 0.023$, $p = 0.123$). However, at country-level, this association varied from negative to positive (95% PI = -0.172 to 0.220). In countries with a higher than average prevalence of intense SMU, intense users reported higher life satisfaction than non-intense users, whereas in countries with a lower than average prevalence, intense users reported lower life satisfaction than non-intense users ($B$ = 1.229, $p$ < 0.001; Figure 4.2B). This cross-level interaction explained 80.0% of the country-variance in this association. Adding the country-level prevalence of problematic SMU as additional cross-level interaction did not improve model fit (Table 4.2, $M1_e$).

Intense users reported more frequent psychological complaints than non-intense users ($B$ = 0.110, $p$ < 0.001), although this was not observed in all countries (95% PI = -0.030 to 0.248). The higher the country-level prevalence of intense SMU, the smaller the difference in psychological complaints between intense and non-intense users, with no differences observed in the highest prevalence countries ($B$ = -0.533, $p$ = 0.002; Figure 4.2B). Although this cross-level interaction only improved AIC, but not BIC (Table 4.2, $M2_d$), it explained 40.0% of the country-variance in this association. Adding the country-level prevalence of problematic SMU as additional cross-level interaction did not improve model fit (Table 4.2, $M2_e$).

### *School Wellbeing*

On average, intense SMU was negatively associated with school satisfaction ($B$ = -0.064, $p$ < 0.001) and positively with school pressure ($B$ = 0.055, $p$ < 0.001), although these associations were close to zero. In some countries, the negative association with school satisfaction and the positive association with school pressure were stronger (95% PIs = -0.152 to 0.024 and -0.033 to 0.143, respectively). These country-variances were not related to the country-level prevalence of intense and problematic SMU, because models including these cross-level interactions did not show better model fit (Table 4.2, $M3_{d,e}$ and $M4_{d,e}$).

### *Social Wellbeing*

Intense and non-intense users reported about similar levels of family support on average ($B$ = 0.039, $p$ = 0.016). However, there was variation in this association, with intense SMU being positively related to family support in some countries and negatively related in other countries (95% PI = -0.145 to 0.227). In countries with a high prevalence of intense SMU, intense users reported more family support than non-intense users, while in countries with a low prevalence, intense users reported less family support than non-intense users ($B$ = 0.816, $p$

< 0.001; Figure 4.2B). This cross-level interaction explained 55.6% of the country-variance in this association. The country-level prevalence of problematic SMU did not explain any country-variance in this association.

In all countries, intense users reported higher levels of friend support than non-intense users ($B$ = 0.327, $p$ < 0.001; 95% PI = 0.115 to 0.545). The higher the country-level prevalence of intense SMU, the stronger this association was ($B$ = 0.786, $p$ < 0.001; Figure 4.2B). This cross-level interaction explained 41.7% of the country-variance in this association. Results also suggested that the relationship between intense SMU and friend support was amplified by country-level prevalence of problematic SMU ($B$ = 1.107, $p$ = 0.036; not shown in Figure). However, the explanatory power of this cross-level interaction was relatively weak, because it explained only 8.3% of the country-variance in this relationship, and it only (marginally) improved AIC, but not BIC (Table 4.2, $M6_e$ relative to $M6_d$).



## Problematic Social Media Use and Wellbeing

Figure 4.3 shows the associations between problematic SMU and all wellbeing outcomes according to the models with the best model fits.

### *Mental Wellbeing*

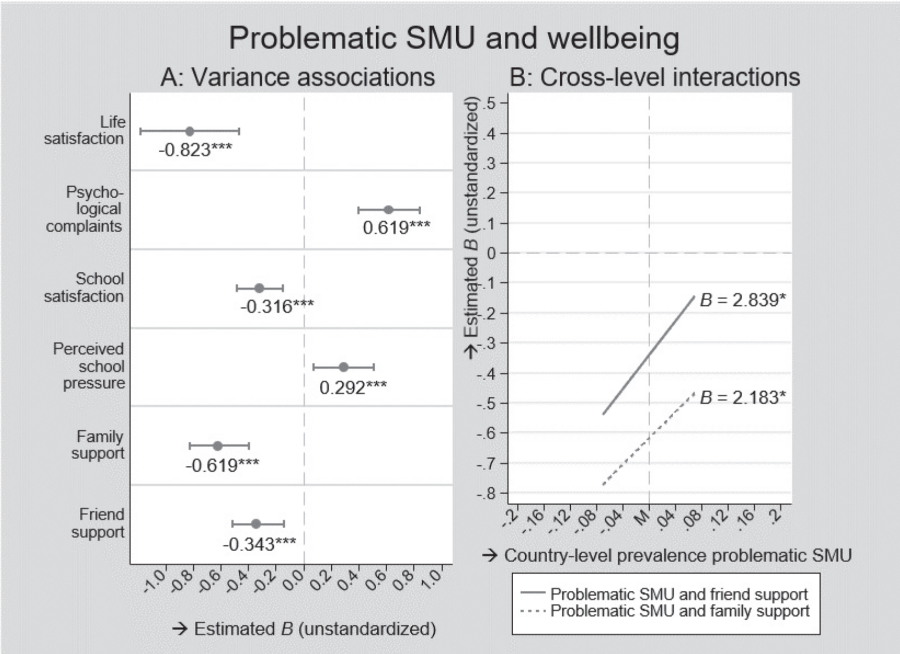
Figure 4.3A shows that, consistent across countries, problematic users reported lower life satisfaction ($B$ = -0.823, $p$ < 0.001; 95% PI = -1.179 to -0.467) and more frequent psychological complaints ($B$ = 0.619, $p$ < 0.001; 95% PI = 0.396 to 0.842) than non-problematic users, although the strength of these associations varied across countries. This country-variance was not related to the country-level prevalence of intense and problematic SMU, as adding these cross-level interactions did not improve model fit (Table 4.2, $M1_{f,g}$ and $M2_{f,g}$).

### *School Wellbeing*

Across all countries, problematic users reported lower school satisfaction ($B$ = -0.316, $p$ < 0.001; 95% PI = -0.480 to -0.152) and higher school pressure ($B$ = 0.292, $p$ < 0.001; 95% PI = 0.077 to 0.507). The observed country-variances in the strength of these associations were not explained by country-level prevalence of intense and problematic SMU, because adding these cross-level interactions did not improve model fit (Table 4.2, $M3_{f,g}$ and $M4_{f,g}$).

**Figure 4.3**

*Associations Between Problematic SMU and Wellbeing*




*Notes.* SMU = social media use; B = unstandardized coefficient; M = mean.
Left (A): dots denote average estimated associations between problematic SMU and the wellbeing outcomes, horizontal lines through the dots denote their 95% prediction interval.
Right (B): diagonal lines represent the estimated associations of problematic SMU and the wellbeing outcomes by the country-level prevalence of problematic SMU. Cross-level interactions were reported when they improved model fit and when they were significant at $p < 0.05$. All estimates were derived from multilevel regression models (Appendix, Table A4.1).
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

## *Social Wellbeing*

In all countries, problematic users reported less family support than non-problematic users ($B$ = -0.619, $p$ < 0.001; 95% PI = -0.826 to -0.396). The higher the country-level prevalence of problematic SMU, the weaker this association was ($B$ = 2.183, $p$ = 0.026; Figure 4.3B). This cross-level interaction explained 25.0% of the country-variance in this association. The country-level prevalence of intense SMU did not explain any country-variance in this association.

In all countries, problematic users reported lower levels of friend support than non-problematic users ($B$ = -0.343, $p$ < 0.001; 95% PI = -0.516 to -0.144). The higher the country-level prevalence of problematic SMU, the weaker this association was ($B$ = 2.839, $p$ = 0.011; Figure 4.3B), which explained 33.3% of the country-variance in this association. The country-level prevalence of intense SMU did not explain any country-variance in this association.

## Cross-National Differences in the Prevalence of Intense and Problematic Social Media Use



Table 4.3 shows that the prevalence of intense SMU varied from 17.35% (Switzerland) to 49.87% (Italy), while the prevalence of problematic SMU varied from 3.22% (the Netherlands) to 14.17% (Spain). Costs of mobile broadband and internet speed did not explain these differences in the country-level prevalence of intense SMU ($B$ < 0.001, $p$ = 0.628; $B$ = -0.005, $p$ = 0.254) and problematic SMU ($B$ = < 0.001, $p$ = 0.568; $B$ = -0.001, $p$ = 0.338).

**Table 4.3**

*Prevalence by Country*

| Country | *N* | Intense SMU | Problematic SMU |
|---|---|---|---|
| Spain | 4,070 | 38.37% | 14.17% |
| Wales | 1,5456 | 37.26% | 11.99% |
| Ireland | 3,628 | 38.72% | 11.99% |
| Italy | 4,069 | 49.87% | 10.56% |
| Finland | 3,067 | 27.08% | 10.16% |
| Greece | 3,715 | 34.06% | 9.93% |
| Scotland | 4,916 | 39.31% | 9.45% |
| Norway | 3,053 | 39.46% | 9.14% |
| Belgium (French) | 3,695 | 38.32% | 8.02% |
| Lithuania | 3,685 | 40.90% | 7.78% |
| England | 3,306 | 33.91% | 7.60% |
| Poland | 5,055 | 43.25% | 7.60% |
| France | 8,621 | 36.82% | 7.59% |
| Luxembourg | 3,889 | 34.83% | 7.37% |
| Canada | 12,355 | 35.33% | 6.71% |
| Belgium (Flanders) | 4,117 | 43.29% | 6.65% |
| Portugal | 5,866 | 40.36% | 5.92% |
| Estonia | 4,622 | 31.42% | 5.79% |
| Hungary | 3,715 | 23.58% | 5.39% |
| Latvia | 4,143 | 25.95% | 5.38% |
| Germany | 4,126 | 26.15% | 5.35% |
| Czech Republic | 11,162 | 21.97% | 5.33% |
| Slovenia | 5,126 | 31.58% | 5.31% |
| Sweden | 4,006 | 43.10% | 5.31% |
| Austria | 4,011 | 33.18% | 4.86% |
| Iceland | 6,693 | 34.14% | 4.83% |
| Switzerland | 7,122 | 17.35% | 4.47% |
| Denmark | 3,113 | 35.04% | 4.12% |
| Netherlands | 4,579 | 27.53% | 3.22% |
| Average | 154,981 | 34.03% | 7.38% |

*Notes.* SMU = social media use; Countries were sorted on their problematic SMU prevalence.

## Discussion

Using data from 29 countries, the present study showed that adolescents' intense SMU was positively or negatively associated with their wellbeing, dependent on the wellbeing domain and national context, whereas problematic SMU was indicative of low wellbeing on all investigated domains and in all countries. More specifically, in countries with a low prevalence of intense SMU, intense users reported more frequent psychological complaints, lower life satisfaction, and lower levels of family support. However, in countries with a high intense SMU prevalence, intense SMU was weakly or not associated with psychological complaints, and was positively related to family support and life satisfaction. Only in some countries, intense users reported lower school satisfaction and higher school pressure than non-intense users, but this did not depend on the country-level prevalence rates of either intense or problematic SMU. Intense SMU was related to higher levels of friends support across all countries, and this association became stronger as country-level prevalence of intense SMU increased.

Findings for problematic SMU were much more consistent than for intense SMU, with lower levels of mental, school, and social wellbeing among problematic users in all countries, although there was country-variance in the strength of these associations. This variance could not be explained by the country-level prevalence of intense and problematic SMU, except for the negative association between problematic SMU and social wellbeing (i.e., family support and friend support), which was stronger in countries with a lower prevalence of problematic SMU. In addition, although countries' prevalence rates of intense and problematic SMU differed substantially, these differences were not explained by the countries' mobile internet accessibility.

By highlighting that the relationship between intense SMU and adolescent wellbeing depends on the wellbeing indicator and the national context, our results challenge the notion that intense SMU is related to lower wellbeing (Primack & Escobar-Viera, 2017; Twenge, Joiner, et al., 2018; Underwood & Ehrenreich, 2017). Our results support findings from systematic reviews showing that SMU can be positively and negatively associated with wellbeing (Best et al., 2014; Verduyn et al., 2017). In fact, given that in countries with high levels of intense SMU intense users reported higher life satisfaction and higher levels of family support than non-intense users, and that in all countries intense users reported higher levels of friend support than non-intense users, intense SMU may often even reflect social engagement, participation, and inclusion, rather than a risk behavior.

In contrast, our findings emphasize the potential harm of problematic SMU, as problematic SMU was negatively associated with all wellbeing domains across all countries. This finding underlines the importance of considering intense SMU and problematic SMU as two different phenomena. The results thereby concur with previous studies showing that, while intense SMU does not necessarily indicate lower wellbeing, problematic SMU seems to be negatively related to multiple domains of wellbeing (Boer, Stevens, et al., 2020; Marino et al., 2018b; Shensa et al., 2017; Van den Eijnden et al., 2018). Hence, risks to wellbeing may arise, not from the time spent on SMU per se, but rather from the distinguishing features of problematic SMU, such as loss of control over SMU and preoccupation with SMU. It therefore seems pivotal to consider problematic SMU as a confounder when investigating the relationship between SMU intensity and wellbeing, as the two SMU concepts are correlated, but have different associations with adolescent wellbeing. Previous reports of negative associations between SMU and wellbeing (Kelly et al., 2018; Primack & Escobar-Viera, 2017) were therefore potentially driven by unobserved problematic SMU.

The finding that intense SMU was mainly negatively associated with wellbeing in countries where the prevalence of intense SMU was low, and that a low country-level prevalence of problematic SMU strengthened the negative association between problematic SMU and social wellbeing, is in line with other cross-national findings on adolescent wellbeing. For example, research suggests that the negative relationship between bullying victimization and life satisfaction is strongest in schools and countries where the prevalence of bullying victimization is low (Arnarsson & Bjarnason, 2018). These findings suggest that normalization theory, which posits that substance use may not necessarily indicate problematic profiles in contexts where it is relatively prevalent (Haskuka et al., 2018; Pennay & Measham, 2016; Sznitman et al., 2015), may be extended to other behaviors. That is, there may be a general pattern where specific adolescent 'risk' behaviors are less indicative of problems, such as lower wellbeing, in contexts where many adolescents show these 'risky' behaviors.

Finally, the finding that countries' mobile internet accessibility did not explain differences in country-level prevalence of intense and problematic SMU suggests that a favourable internet access does not increase risks related to SMU. Cross-national differences in the prevalence of intense and problematic SMU may be better explained through countries' prevailing cultural and social norms and rules regarding (social) media use, which may influence the extent to which schools and parents restrict adolescents' SMU and educate adolescents in digital literacy. However, empirical research is required to verify this possible explanation.

## Strengths and Limitations

The present study has important strengths related to the number of included countries, the representative nature of the data, and the conceptual distinction between intense and problematic SMU. However, our findings should be interpreted with caution, because mental, school, and social wellbeing were measured using either single or a few items. The use of such measures may have limited the representations of the wellbeing constructs, and reliability could not be established for the single-item measures. Hence, more research that replicates our study using more detailed measures of wellbeing is warranted. In addition, the cross-sectional design of the study does not allow for causal inferences. A reverse pattern whereby low wellbeing induces problematic SMU, also may be plausible (Marino et al., 2018b). While some longitudinal studies provide evidence for a causal pathway whereby problematic SMU would negatively affect (mental) wellbeing (Boer, Stevens, et al., 2020; Van den Eijnden et al., 2018), other research suggests a reverse (Raudsepp & Kais, 2019) or bidirectional pathway (Li et al., 2018). Also, all measures were based on self-reports which may deviate from, for example, actual frequency of SMU (Orben & Przybylski, 2019a, 2019b). Further, our measure of intense SMU was a measure of active SMU (i.e., using social media to communicate), and not of passive SMU (i.e., scrolling through profiles). A different measure of intense SMU that includes passive use may have yielded different results, as research suggests that passive use mainly decreases wellbeing (Verduyn et al., 2015; Wenninger et al., 2014), while active usage may enhance wellbeing (Verduyn et al., 2017). Taking these limitations into account, longitudinal research on the direction of the association between (problematic) SMU and wellbeing, using more specific and objective measures of SMU, such as smartphone application tracking apps, are important directions for future research.

## Conclusion

Notwithstanding the previously mentioned limitations, the finding that adolescents throughout 29 countries who report problematic SMU are particularly at risk for impairments in wellbeing, is highly relevant to current policies and guidelines for healthy SMU. Schools, family, and clinical settings are potential contexts for the detection of adolescents with problematic SMU, as well as for the implementation of support and interventions aimed at reducing the levels of problematic SMU. Additional support may be provided to adolescents reporting intense SMU in countries with a low prevalence of intense SMU, because they may also be vulnerable to lower wellbeing.

# Appendix

**Table A4.1**

*Multilevel Unstandardized Results ($n_{individuals}$ = 154,981, $n_{countries}$ = 29)*

| | Mental wellbeing | | | | School wellbeing | | | | Social wellbeing | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | M1$_d$ Life satisfaction | | M2$_d$ Psychological complaints | | M3$_c$ School satisfaction | | M4$_c$ School pressure | | M5$_g$ Family support | | M6$_g$ Friends support | |
| ***WITHIN*** | ***B*** | ***(SE)*** | ***B*** | ***(SE)*** | ***B*** | ***(SE)*** | ***B*** | ***(SE)*** | ***B*** | ***(SE)*** | ***B*** | ***(SE)*** |
| Intense SMU | 0.023 | (0.015) | 0.110*** | (0.012) | -0.064*** | (0.010) | 0.055*** | (0.010) | 0.039* | (0.016) | 0.327*** | (0.019) |
| Problematic SMU | -0.823*** | (0.038) | 0.619*** | (0.024) | -0.316*** | (0.017) | 0.292*** | (0.021) | -0.619*** | (0.027) | -0.343*** | (0.026) |
| ***CROSS-LEVEL*** | ***B*** | ***(SE)*** | ***B*** | ***(SE)*** | ***B*** | ***(SE)*** | ***B*** | ***(SE)*** | ***B*** | ***(SE)*** | ***B*** | ***(SE)*** |
| Intense SMU × intense SMU prevalence | 1.229*** | (0.271) | -0.533** | (0.171) | | | | | 0.816*** | (0.234) | 0.786*** | (0.218) |
| Intense SMU × problematic SMU prevalence | | | | | | | | | 0.947 | (0.607) | 1.107* | (0.526) |
| Problematic SMU × intense SMU prevalence | | | | | | | | | -0.422 | (0.380) | -0.460 | (0.338) |
| Problematic SMU × problematic SMU prevalence | | | | | | | | | 2.183* | (0.977) | 2.839* | (1.118) |
| ***MODEL FIT*** | **Estimate** | | **Estimate** | | **Estimate** | | **Estimate** | | **Estimate** | | **Estimate** | |
| Free parameters[1] | 23 | | 23 | | 22 | | 22 | | 26 | | 26 | |
| AIC | 616002.8 | | 430723.3 | | 383745.5 | | 399546.0 | | 597158.6 | | 597480.0 | |
| BIC | 616231.7 | | 430952.2 | | 383964.4 | | 399764.9 | | 597417.4 | | 597738.8 | |
| ***RANDOM PARAMETERS*** | **Estimate** | ***(SE)*** | **Estimate** | ***(SE)*** | **Estimate** | ***(SE)*** | **Estimate** | ***(SE)*** | **Estimate** | ***(SE)*** | **Estimate** | ***(SE)*** |
| Variance between individuals | 3.117*** | (0.079) | 0.943*** | (0.020) | 0.696*** | (0.022) | 0.771*** | (0.023) | 2.759*** | (0.234) | 2.765*** | (0.167) |
| Variance between countries | 0.021*** | (0.006) | 0.021*** | (0.006) | 0.024** | (0.008) | 0.035* | (0.014) | 0.136*** | (0.030) | 0.174*** | (0.043) |
| (Residual) variance intense SMU | 0.002 | (0.001) | 0.003** | (0.001) | 0.002** | (0.001) | 0.002* | (0.001) | 0.003* | (0.002) | 0.006 | (0.003) |
| (Residual) variance problematic SMU | 0.034** | (0.011) | 0.013* | (0.006) | 0.007** | (0.002) | 0.012 | (0.008) | 0.009* | (0.004) | 0.006 | (0.003) |
| 95% PI intense SMU[2] | [-0.172 / 0.220] | | [-0.030 / 0.248] | | [-0.152 / 0.024] | | [-0.033 / 0.143] | | [-0.145 / 0.227] | | [0.115 / 0.545] | |
| 95% PI problematic SMU[2] | [-1.179 / -0.467] | | [0.396 / 0.842] | | [-0.480 / -0.152] | | [0.077 / 0.507] | | [-0.826 / -0.396] | | [-0.516 / -0.144] | |
| $R^2$ random slope intense SMU | 80.00% | | 40.00% | | | | | | 55.56% | | 41.67% + | 8.33% |
| $R^2$ random slope problematic SMU | | | | | | | | | 25.00% | | 33.33% | |

*Notes.* SMU = social media use; M = model; PI = prediction interval; $R^2$ = explained variance.

[1] Parameters not shown in table (16): control variables female, family affluence, and age, the random intercept of the respective wellbeing indicator, effects of the country-level prevalence of intense and problematic SMU on the random intercept, the covariances between the random intercept and the random slopes, effects of country-level costs of mobile broadband and internet speed on country-level prevalence of intense and problematic SMU, the intercepts of the country-level prevalence of intense and problematic SMU, and the residual variances of the country-level prevalence of intense and problematic SMU.

[2] Based on *B*'s and variance parameters of models without cross-level effects (Table 4.2, M1-6$_c$).

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

# CHAPTER 5

# ATTENTION DEFICIT HYPERACTIVITY DISORDER-SYMPTOMS, SOCIAL MEDIA USE INTENSITY, AND SOCIAL MEDIA USE PROBLEMS IN ADOLESCENTS: INVESTIGATING DIRECTIONALITY

Maartje Boer, Gonneke W. J. M. Stevens, Catrin Finkenauer, and Regina J. J. M. van den Eijnden

**Author Contributions**

All authors conceived of the study. MB conducted the literature review, data analyses, and drafted the initial and revised manuscript. RvdE initiated and coordinated the data collection of the data from the present study. GS, CF, and RvdE critically reviewed all sections of the initial and revised manuscript and advised during all stages of the manuscript preparation. All authors approved of the final manuscript.

**Publication**

Boer, M., Stevens, G. W. J. M., Finkenauer, C., & Van den Eijnden, R. J. J. M. (2020). Attention deficit hyperactivity disorder-symptoms, social media use intensity, and social media use problems in adolescents: Investigating directionality. *Child Development 91*(4), e853-865. https://doi.org/10.1177/10731911211027232

# Abstract

Cross-sectional research shows that adolescents' social media use (SMU) and Attention Deficit Hyperactivity Disorder (ADHD)-symptoms are related, but it is unclear whether this relation is explained by SMU intensity or by addiction-like SMU problems. Also, due to the lack of longitudinal studies, the direction of this relation remains unknown. This study aims to disentangle which type of SMU is related to ADHD-symptoms, and in which direction, using a three-wave longitudinal study among Dutch adolescents aged 11–15 years ($n$ = 543). Findings suggest a unidirectional relation: SMU problems increased ADHD-symptoms over time, SMU intensity did not. This implies that problematic use, rather than the intensity of use harmfully affects adolescents' ADHD-symptoms.


*Keywords*: ADHD, social media use, problematic social media use, social media addiction, adolescents.

# Attention Deficit Hyperactivity Disorder-symptoms, Social Media Use Intensity, and Social Media Use Problems in Adolescents: Investigating Directionality

Social media use (SMU), such as the use of Instagram and Snapchat, has increased over the last few years, especially among adolescents (Anderson & Jiang, 2018; Kloosterman & Van Beuningen, 2015). In 2018, 45% of the adolescents in the United States aged 13-17 reported being online almost constantly, while in 2015 this was 24% (Anderson & Jiang, 2018). Although SMU enables adolescents to stay involved with peers and facilitates engagement in online social activities (Kuss & Griffiths, 2011; Ryan & Xenos, 2011), scholars have raised concerns that SMU may increase symptoms of Attention Deficit Hyperactivity Disorder (ADHD) in youth (Cabral, 2011; Levine et al., 2007, 2012). However, it remains unclear which aspect of SMU would drive this association. To enhance our understanding of whether and how SMU and ADHD-symptoms are related, the present study distinguished between *SMU intensity* and *SMU problems*. SMU intensity refers to the frequency of use, whereas SMU problems are characterized by addiction-like behaviors, such as the displacement of other activities for SMU, or having conflicts with others due to their SMU (Griffiths et al., 2014; Van den Eijnden et al., 2016). Although adolescents with SMU problems typically report high SMU intensity (Van den Eijnden et al., 2018), high SMU intensity does not necessarily impair important life domains to the same extent as SMU problems.

Cross-sectional research showed that adolescents who reported high SMU intensity, also reported more ADHD-symptoms (Barry et al., 2017; Levine et al., 2007). Other studies found associations between SMU problems and ADHD-symptoms (Andreassen et al., 2016; Mérelle et al., 2017; Van den Eijnden et al., 2016; Wu et al., 2013). These findings raise two questions. First, it remains unclear whether SMU intensity, SMU problems, or both relate to ADHD-symptoms, because existing studies examined SMU intensity and SMU problems separately. Nevertheless, these two types of SMU are correlated (Van den Eijnden et al., 2016, 2018). Although theoretically both types of SMU can be related to ADHD-symptoms, research has shown that SMU intensity and SMU problems can generate different outcomes over time (Van den Eijnden et al., 2018). Therefore, the first aim of the present study is to explore whether the two types of SMU relate to ADHD-symptoms. Second, given the cross-sectional nature of previous research, the directions of the relations between social media behaviors and ADHD-symptoms remain unknown. Using data from a longitudinal study, the present study addresses these gaps in our knowledge.

Recently, scholars have cautioned against over-pathologizing normative behaviors, questioning whether problematic internet-related behaviors, as defined by substance addiction criteria, cause significant harm (Kardefelt-Winther et al., 2017; Van Rooij et al., 2018). Yet, recent longitudinal research suggests that SMU problems impair life satisfaction over time, while SMU intensity does not (Van den Eijnden et al., 2018). The current study extends this research by exploring whether SMU intensity and SMU problems independently, or in concert, increase ADHD-symptoms.

## The Influence of ADHD-symptoms on SMU Intensity and SMU Problems

ADHD is characterized by three behavioral components: attention deficits, hyperactivity, and impulsivity. Adolescents with attention deficits often experience difficulties in completing tasks that require a long attention span, because they easily become distracted. Adolescents with hyperactive behavior typically show physical restlessness. Impulsive adolescents tend to have a strong preference for immediate rewards over delayed rewards, and often act without deliberate forethought (American Psychiatric Association, 2013).

Social media afford several features that may be particularly attractive to adolescents with ADHD-symptoms. First, they can be used through smartphones at any time and at any place, and social media applications on smartphones actively notify users of incoming messages and updated content (Pielot et al., 2014). Social media may therefore be tempting external distractors in daily life to which adolescents with ADHD-symptoms are more sensitive than adolescents without symptoms (American Psychiatric Association, 2013). Second, social media allow adolescents to navigate through profiles quickly and to engage in multiple conversations at the same time, facilitating quick rewards to immediate informational and social needs. We therefore expected that *high levels of ADHD-symptoms increase SMU intensity over time (H1).* Furthermore, ADHD-symptoms constitute a risk factor for developing addictions, such as substance dependency (Cyders & Smith, 2009; Ohlmeier et al., 2008). Because SMU problems are characterized by addiction-like behaviors, adolescents with ADHD-symptoms may also be sensitive to developing SMU problems. We therefore expected that *high levels of ADHD-symptoms increase SMU problems over time (H2).*

## The Influence of SMU Intensity and SMU Problems on ADHD-symptoms

Adolescents who intensively use social media may be accustomed to task-switching between media activities and other (offline or online) activities (Karpinski et al., 2013; Rosen et al., 2013). This may impair their ability to filter relevant from irrelevant information, which may, in turn, contribute to the development of attention deficits (Baumgartner et al., 2017). Also, intensive social media users may become habituated to the entertainment provided by social media. As a result, they may perceive activities without media that require prolonged attention as unentertaining or boring, resulting in experiences of attention deficits (Nikkelen et al., 2014). Furthermore, intensive SMU may disrupt sleep due to intensive exposure to bright screens (Van der Schuur et al., 2018), which, in turn, could lead to more attention deficits or to impaired abilities to forego immediate impulses at daytime (Fallone et al., 2001). We thus expected that *SMU intensity increases ADHD-symptoms over time (H3).* Also, adolescents with SMU problems may experience attention deficits due to their preoccupation with social media. Their constant urge to go online may make them feel restless when they cannot immediately check and respond to incoming messages, for example, at school. We therefore expected that *SMU problems increase ADHD-symptoms over time (H4).*

## Current Study

The current study investigated the directionality of associations between ADHD-symptoms and both SMU intensity and SMU problems, using three waves of longitudinal data on Dutch secondary-school adolescents aged 11-15 years (Van den Eijnden et al., 2018). To address directionality, we applied the 'random intercept cross-lagged panel model' (RI-CLPM) (Hamaker et al., 2015). This novel modelling technique allowed us to examine relations between social media behaviors and ADHD-symptoms over time, while controlling for all possible confounding stable characteristics, such as personality traits. The technique draws on a multilevel approach by disentangling within- and between-person variance, allowing for more accurate estimations of directionality (Hamaker et al., 2015).

# Method

## Sample

To examine our hypotheses, we used the first three waves of the Digital Youth-project; a longitudinal study on online behaviors and mental health among secondary school students based on self-report measures (Van den Eijnden et al., 2018). The study was conducted in February and March of 2015, 2016, and 2017, respectively. In the first wave, 543 adolescents from the first and second year of two secondary schools participated in the study. Both schools were based in the Netherlands: one school was located in medium-sized city and the other was located in a large city. Participants were between 11 and 15 years old ($M_{age}$ = 12.91, $SD_{age}$ = 0.73). Of this sample, 293 adolescents (54%) participated in all three waves, 198 (36%) in two waves, and 52 (10%) in one wave. Non-response was mainly due to dropout of entire school classes and not due to individual selection, because teachers were absent, or because teachers were not able to schedule time for the completion of the survey. During the first wave, school year and gender were evenly distributed (51% first year students, 52% girls). Adolescents attending pre-university education (48%) and adolescents with two Dutch parents (84%) were somewhat overrepresented compared to the composition of the Dutch adolescent population in the first two years of secondary school (26% and 73%, respectively) (Central Bureau for Statistics, 2018b).

Survey participation occurred through digital self-completion during school hours and was voluntary and anonymous. Participants did not receive any incentives. Research assistants were present during assessments to assist when necessary. Participants were instructed that they were allowed to quit the survey at any time during assessment. Parents received information letters prior to survey participation, which provided them with the opportunity to refuse participation of their child. The study procedures were carried out in accordance with the Declaration of Helsinki and were approved by the board of ethics of the Faculty of Social Sciences at Utrecht University (FETC16-076 Eijnden).

## Measures

### *SMU Intensity*

Four items on the use of social network sites and instant messengers were used to measure SMU intensity (Van den Eijnden et al., 2018). Respondents were asked "How many times a *day* do you check social network sites?", "How many times a *week* do you 'like' messages, photos, or movies from others on social network sites?", "How many times a *week* do you send out a response to (or share) messages, photos, or movies from others on social network sites?". Examples of social network sites were provided in the questionnaire (Facebook, Twitter, Instagram, Google+, or Pinterest). Respondents answered on a 7-point scale, where high values indicate high SMU intensity (1 = *less than once a day* and 7 = *more than 40 times*). The fourth item referred to instant messenger use: "How many times a *day* do you send a message, photo or movie via your smartphone, via for example WhatsApp, Chat, SnapChat or SMS?" (1 = *less than once a day* and 7 = *more than 80 times*). Factor loadings of all items ranged between 0.68 and 0.82 across all three waves. Cronbach's α values were 0.86 (T1), 0.85 (T2), and 0.84 (T3). The original scale consisted of six items. Items "How many times a week do you post a message, photo, or movie, on social network sites?" and "How many times a day do you check your smartphone on messages, photo's, or videos, via for example WhatsApp, Chat, SnapChat or SMS?" were excluded due to having factor loadings below 0.5, and high intercorrelation ($r$ = 0.70) with another item, respectively.

### *SMU Problems*

The Social Media Disorder-scale was used to measure SMU problems (Van den Eijnden et al., 2016). The scale includes nine items corresponding to the nine diagnostic criteria for Internet Gaming Disorder according to the Appendix of the DSM-5 (American Psychiatric Association, 2013; Lemmens et al., 2015). These criteria entail preoccupation, persistence, tolerance, withdrawal, displacement, escape, problems, deception, and conflict, which are in line with criteria for substance dependence. Adolescents were asked "During the past year, have you (...)", followed by, for example, "regularly had no interest in hobbies or other activities because you would rather use social media?", which refers to the criterion 'displacement'. Respondents replied on a dichotomous scale (1 = *yes* and 0 = *no*). High values on the scale indicated a high level of SMU problems. Factor loadings ranged between 0.52 and 0.85 across all three waves. Prior validation research showed that the SMD-scale had medium to large positive correlations with compulsive internet use and self-declared social media addiction, confirming adequate convergent validity (Van den Eijnden et al., 2016). The scale was also found to have small to moderate positive correlations with mental health problems and frequency of SMU, confirming satisfactory criterion validity (Van den Eijnden et al., 2016). Given the dichotomous nature of the items, internal consistency was calculated using the ordinal alpha that is based on the tetrachoric correlation matrix (Gadermann et al., 2012). Ordinal alpha values were 0.83 (T1), 0.90 (T2), and 0.89 (T3).

#### *ADHD-Symptoms*

The ADHD-Questionnaire was selected for use in this study, as it has been shown to be a reliable and valid measure of ADHD-symptoms in adolescent populations (Scholte & Van der Ploeg, 1999). In order to gain insight into which ADHD-symptoms related to social media behaviors, the three symptoms of ADHD were measured separately. *Attention deficits* was measured using nine items, for example "I avoid tasks that require prolonged effort". Factor loadings ranged between 0.60 and 0.79; Cronbach's α values were 0.89 (T1), 0.90 (T2) and 0.87 (T3). *Impulsivity* was indicated by six items, such as "I find it difficult to wait for my turn". Factor loadings ranged between 0.55 and 0.77; Cronbach's α values were 0.79 (T1), 0.83 (T2), and 0.81 (T3). Six items were used to measure *hyperactivity*, for example "I feel restless". Factor loadings ranged between 0.47 and 0.85; Cronbach's α values were 0.85 (T1), 0.88 (T2), and 0.82 (T3). Respondents replied on five-point response scales, where high values indicated higher levels of ADHD-symptoms (1 = *never* and 5 = *very often*).

### Measurement Invariance Over Time

To draw conclusions on effects over time, identical constructs should be measured across all three waves. Therefore, *measurement invariance* analyses were conducted prior to the analyses, using Mplus 8.1 (L. K. Muthén & Muthén, 2017b). For each measure, this was done by means of multigroup confirmatory factor analysis (CFA) on the data structured in long format ($n$ = 1,629), where groups were indicated by waves. Measurement invariance was imposed by constraining the loadings and intercepts of the items to be equal across all waves, after which model fit was evaluated. For SMU problems, thresholds instead of intercepts were constrained to be equal, because this scale consists of binary items. Measurement invariance analyses for SMU intensity, attention deficits, impulsivity, and hyperactivity were carried out using Maximum Likelihood estimation with robust standard errors (MLR), which corrects for the somewhat skew distributions of these measures. For SMU problems, Weighted Least Square Means and Variance Adjusted (WLSMV)-estimation was used, which is recommended for categorical items (L. K. Muthén & Muthén, 2017b). For each multigroup CFA, overall model fit was evaluated using the Comparative Fit Index (CFI; > 0.9 = acceptable; > 0.95 = excellent), Tucker Lewis Index (TLI; > 0.9 = acceptable; > 0.95 = excellent), and Root Mean Square Error of Approximation (RMSEA; < 0.08 = acceptable; < 0.05 = excellent) (Van de Schoot et al., 2012). We subsequently evaluated whether removing the equality constraints on the loadings and intercepts/thresholds would significantly improve model fit based on change in CFI (increase of ≥ 0.010) and RMSEA (decrease of ≥ 0.015) (F. F. Chen, 2007). In measurement invariance analyses, evaluation of model fit using ΔCFI and ΔRMSEA are preferred over $\chi^2$-difference tests, because the latter is sensitive to large sample sizes (F. F. Chen, 2007; Cheung & Rensvold, 2002).

Table 5.1 shows that when measurement invariance over time was imposed, the overall model fits of the multigroup CFA models for SMU intensity, SMU problems, attention deficits, and impulsivity were all acceptable to excellent. Model fits did not significantly improve when equality constraints on the item loadings and intercepts or thresholds were released. This means that measurement invariance was established for these four measures, and that we can make meaningful conclusions about their longitudinal relations (Van de Schoot et al., 2012). The overall model fit for hyperactivity was relatively low (CFI = 0.874, TLI = 0.879, and RMSEA = 0.122), and measurement invariance was not established (ΔCFI = 0.019). However, additional analyses (results not shown) showed that measurement invariance was only related

5

to the intercepts of two items from the hyperactivity-scale. Hyperactivity was thereby sufficiently invariant over time for the purposes of our analyses (Van de Schoot et al., 2012).

**Table 5.1**

*Measurement Invariance Analysis: Multigroup CFA (n = 1,629)*

| | **Overall model fit constrained model**[1] | | | **Change in model fit**[2] | |
|---|---|---|---|---|---|
| | **CFI** | **TLI** | **RMSEA** | **ΔCFI** | **ΔRMSEA** |
| SMU intensity | 0.989 | 0.989 | 0.047 | 0.009 | -0.010 |
| SMU problems | 0.963 | 0.957 | 0.034 | -0.007 | 0.006 |
| Attention deficits | 0.932 | 0.935 | 0.073 | 0.009 | 0.007 |
| Impulsivity | 0.987 | 0.987 | 0.031 | 0.004 | 0.002 |
| Hyperactivity | 0.874 | 0.879 | 0.122 | 0.019 | 0.026 |

*Notes.* SMU = social media use; CFA = confirmatory factor analysis; CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation.
[1] Multigroup CFA model where item loadings and intercepts/thresholds were constrained to be equal over time.
[2] Compared to multigroup CFA model where item loadings and intercepts/thresholds were free to vary over time.

## Generating Factor Scores

Modelling the RI-CLPM using latent variables for our measures was not feasible, given the complexity of our model related to the large number of latent variables. We therefore considered using the sum-scores of the observed items, which is the most common practice in applications of the RI-CLPM (Hamaker et al., 2015). However, the distribution of the sum-score of SMU problems is heavily skewed (Van den Eijnden et al., 2016), which often leads to biased results in statistical analyses (Hox et al., 2010). Moreover, sum-scores do not consider that items have different contributions to their latent measure, as reflected by their different factor loadings, which may lead to inaccurate representations of latent measures (Distefano et al., 2009). We addressed these shortcomings by using *factor scores* instead of sum-scores, which are imputed values that reflect plausible values of latent measures based on the CFA-model (Distefano et al., 2009).

Factor scores were computed using Mplus 8.1 (L. K. Muthén & Muthén, 2017b). For all five measures separately, CFA-models with three latent measures were specified, referring to the three repeated measures in wide format ($n$ = 543). In these models, measurement invariance over time was imposed, and means of the latent measures were freely estimated. Factor scores according to these CFA-models were computed and saved. The saved factor scores were subsequently used as observed variables for the RI-CLPM. Factor scores of

SMU intensity, attention deficits, impulsivity, and hyperactivity were computed using MLR-estimation. WLSMV-estimation was used to compute factor scores of SMU problems. Factor scores for participating as well as dropout cases were calculated based on all available data on previous wave(s). For example, for respondents that dropped out in the second wave, regression methods were used to estimate factor scores at the second wave using the respondents' available scores at the first and third wave and the estimated model parameters (B. O. Muthén, 2004). Therefore, all 543 participants were retained in the analysis. Table 5.2 shows the descriptive statistics of the factor scores for all five measures in long format ($n$ = 1,629).



**Table 5.2**

*Descriptive Statistics, Factor Scores (n = 1,629)*

| | *M* [95% CI] | *SD* | Minimum | Maximum |
|---|---|---|---|---|
| SMU intensity | 0.22 [0.16, 0.28] | 1.22 | -2.62 | 2.53 |
| SMU problems | 0.14 [0.12, 0.17] | 0.49 | -0.44 | 2.14 |
| Attention deficits | 0.12 [0.09, 0.16] | 0.76 | -1.37 | 2.95 |
| Impulsivity | 0.01 [-0.01, 0.04] | 0.54 | -0.87 | 2.52 |
| Hyperactivity | 0.02 [-0.02, 0.06] | 0.81 | -1.17 | 2.89 |

*Notes.* SMU = social media use; *M* = mean; CI = confidence interval; *SD* = standard deviation.

Differences between participating and dropout participants were analyzed by predicting drop-out in T2 and T3 with the computed factor scores of previous wave(s). Multivariate logistic regression (results not shown) showed that adolescents who reported high SMU intensity in T1 were more likely to dropout in T3 (OR = 1.34, $p < 0.05$), although this only explained a small proportion of the variance in T3 dropout (Nagelkerke $R^2 = 0.010$). SMU problems, attention deficits, impulsivity, and hyperactivity were not related to dropout in any of the waves.

## Modelling Strategy

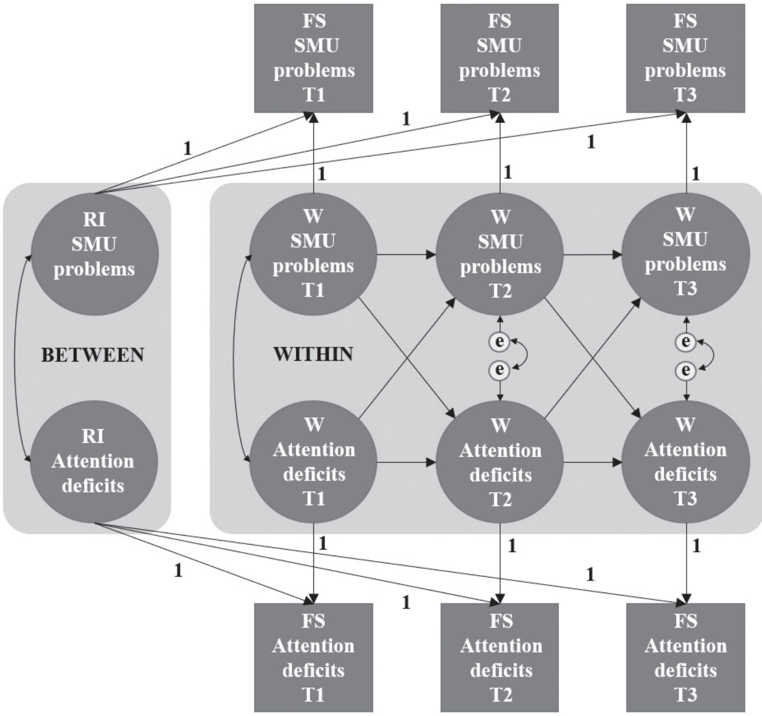
Directionality can be established by examining whether changes in ADHD-symptoms induce changes in social media behaviors, and vice versa, which refers to a dynamic process that takes place within adolescents. To study these dynamics within adolescents, between-person variance should be separated from the within-person variance, because time-invariant traits on the between-person level may confound within-person dynamics. The RI-

CLPM partials out all possible confounding time-invariant traits by adding a random intercept for each measure, which captures the stability of the respective measure at the between-person level. As a result, cross-lagged relations in the RI-CLPM solely reflect within-person dynamics that are not confounded by time-invariant traits at the between-person level (Hamaker et al., 2015), such as stable individual differences in temperament.

After measurement invariance was established and factor scores were generated, the RI-CLPM was fitted using Mplus 8.1 with MLR-estimation (Hamaker, 2018; L. K. Muthén & Muthén, 2017b). A two-variable RI-CLPM is illustrated in Figure 5.1. In this study, this model was extended to a five-variable RI-CLPM, including SMU intensity, SMU problems, attention deficits, impulsivity, and hyperactivity (see Appendix, Figure A5.1). The *between-person part* of the RI-CLPM is denoted by the random intercepts. Random intercepts are latent variables that are extracted from the computed factor scores that reflect the same construct over time with loadings fixed to one. Each random intercept represents the person-specific time-invariant stability of the measure. Correlations between all random intercepts were specified. Positive correlations between the random intercepts indicate, for example, that adolescents with high averages in attention deficits also report high averages in SMU problems. The *within-person part* of the RI-CLPM is denoted by within-person values, which are additional latent variables that are extracted from their respective computed factor scores, again with loadings fixed to one. Residual variances of the computed factor scores were constrained to zero. The within-person values denote the adolescent's deviations from their expected score. The expected score at $T_x$ consists of the grand mean of the respective wave and the adolescent's random intercept. Cross-lagged paths, auto-regressive paths, and within-wave (residual) correlations were specified between the within-person values (Figure 5.1). Positive cross-lagged paths indicate, for example, that adolescents whose attention deficits at $T_x$ increased relative to their expected score, also reported increased SMU problems relative to their expected score at $T_{x+1}$. By including auto-regressive paths, the model controls for preceding increases or decreases (e.g., SMU problems at $T_x$ on SMU problems at $T_{x+1}$). By including within-wave (residual) correlations, the model also controls for increases or decreases that occurred simultaneously within the same year (e.g., attention deficits at $T_x$ with SMU problems at $T_x$). In addition, all cross-lagged paths, auto-regressive paths, within-wave (residual) correlations, and means were unconstrained over time. Results of the RI-CLPM were standardized ($STD_{YX}$) to facilitate interpretation of effect sizes.

**Figure 5.1**

*Two-Variable Random Intercept (RI) Cross-Lagged Panel Model*




*Notes.* Squares represent the computed factor scores (FS). Circles represent RIs and within-person (W) values of the respective factor scores. On the within-person level, cross-lagged paths are denoted by the diagonal arrows, auto-regressive paths by the horizontal arrows, and within-wave (residual) correlations by the double-ended arrows. Auto-regressive paths, cross-lagged paths, and within-wave (residual) correlations were estimated freely. On the between-person level, RIs were correlated. In the final analysis, this model was extended with social media use (SMU) intensity, impulsivity, and hyperactivity.

Monte Carlo simulations in Mplus 8.1 were carried out to determine statistical power to reject the null hypothesis of no effect (L. K. Muthén & Muthén, 2002). Power analyses were carried out using 1000 simulated samples, a sample size of $n$ = 543, and a Type I error rate of 0.05. The power analyses were based on our RI-CLPM including free estimation of all cross-lagged effects, auto-regressive effects, and all (residual) correlations. For detection of moderate effects ($\beta$ = 0.3), power ranged between 0.94 and 1.00 for all estimates. For detection of small effects ($\beta$ = 0.2) power ranged between 0.68 and 0.94 for all estimates. We could not derive the minimum relevant effect size from the literature, because no longitudinal studies specifically focusing on social media behaviors and ADHD-symptoms exist. Cross-sectional studies examining the relation between (problematic) SMU and ADHD-symptoms using multivariate models showed small-to-medium effect sizes with $\beta$ = 0.24 on average (Andreassen et al., 2016; Barry et al., 2017; Levine et al., 2007; Mérelle et al., 2017; Wu et al., 2013). For this effect size, power ranged between 0.80 and 0.99 for all estimates in our model. Thus, the analyses showed that our sample size of $n$ = 543 is able to detect effect sizes corresponding to previous cross-sectional studies.

# Results

## Preliminary Results

Prior to the main analysis, preliminary analyses were conducted on the data in long format ($n$ = 1,629) to study the intra-class correlations (ICC's) of our measures. ICC's express the proportion of variance that is explained on the between-person level relative to the total variance, which provides insight into the stability of our measures over time. Table 5.3 shows that the majority of the measures in our study varied mainly between adolescents, especially for SMU problems (89.9%). This means that most of our measures were relatively stable over time. However, a substantial part of the variance of our measures was related to changes within adolescents over time (10.1% to 28.5%).

We also studied how our measures developed over time and whether the measures were related with demographic characteristics by means of multilevel multiple regression ($n$ = 1,629). Table 5.3 shows that on average, SMU intensity, SMU problems, and attention deficits increased in the second and the third wave relative to the first wave. Impulsivity only increased in the third wave relative to the first wave. Hyperactivity did not increase over time, although the ICC indicated that hyperactivity varied across waves Girls reported

**Table 5.3**

*Preliminary Results, Standardized (n = 1,629)*

| | SMU intensity | | | SMU problems | | | Attention deficits | | | Impulsivity | | | Hyperactivity | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | ***β*** | ***SE*** | ***p*** | ***β*** | ***SE*** | ***p*** | ***β*** | ***SE*** | ***p*** | ***β*** | ***SE*** | ***p*** | ***β*** | ***SE*** | ***p*** |
| Wave 2[1] | 0.39 | 0.06 | < 0.001 | 0.84 | 0.05 | < 0.001 | 0.27 | 0.06 | < 0.001 | -0.05 | 0.07 | 0.476 | 0.09 | 0.06 | 0.117 |
| Wave 3[1] | 0.84 | 0.06 | < 0.001 | 0.35 | 0.06 | < 0.001 | 0.67 | 0.07 | < 0.001 | 0.20 | 0.06 | 0.001 | 0.09 | 0.07 | 0.163 |
| Girls[2] | 0.42 | 0.09 | < 0.001 | 0.22 | 0.08 | 0.007 | -0.07 | 0.09 | 0.445 | -0.18 | 0.09 | 0.046 | -0.02 | 0.09 | 0.842 |
| Prevocational education[3] | 0.26 | 0.09 | 0.003 | 0.45 | 0.09 | < 0.001 | 0.25 | 0.10 | 0.010 | 0.28 | 0.09 | 0.003 | 0.26 | 0.10 | 0.007 |
| Native ethnic background[4] | 0.25 | 0.12 | 0.034 | -0.03 | 0.012 | 0.831 | 0.19 | 0.13 | 0.150 | 0.02 | 0.14 | 0.871 | 0.26 | 0.11 | 0.021 |
| ICC[5] | 0.803 | | | 0.899 | | | 0.715 | | | 0.771 | | | 0.756 | | |

*Notes*. SMU = social media use; $\beta$ = standardized coefficient; *SE* = standard error; *p* = p-value; ICC = intraclass correlation. Results represent multilevel multiple regression results estimated with Maximum Likelihood with Robust standard errors (MLR). Observations (*n* = 1,629) were nested in individuals (*n* = 543). Waves were specified on the within-person level; girls, educational level, and ethnic background were specified on the between-person level. All independent covariates are binary, and therefore all coefficients were standardized based on $STD_Y$-standardization.

[1] Reference category = wave 1.

[2] Reference category = boys.

[3] Reference category = intermediate/pre-university education.

[4] Reference category = immigrant background.

[5] ICC = variance between / (variance within + variance between).

.higher SMU intensity and more SMU problems than boys. Girls also experienced less impulsivity than boys. Pre-vocational educated adolescents reported higher SMU intensity, more SMU problems, and more ADHD-symptoms than intermediate or pre-university educated adolescents. Adolescents with two Dutch parents reported more SMU intensity and more hyperactivity than adolescents with at least one parent from another country. These observed mean differences in factor scores do not affect our longitudinal results, because the RI-CLPM controls for all possible time-invariant confounders, which makes adding between-person characteristics as covariates redundant (Hamaker et al., 2015).

## ADHD-Symptoms, SMU Intensity, and SMU Problems

The overall model fit of the RI-CLPM was good (CFI = 0.998; TLI = 0.984; RMSEA = 0.042; $\chi^2(10) = 19.472$, $p = 0.035$). Table 5.4 shows the correlations between the random intercepts. Adolescents with high averages of SMU intensity and with high averages of SMU problems also reported high averages in attention deficits, impulsivity, and hyperactivity (correlations varying from $r = 0.23$ to 0.29, $p = < 0.001$ to 0.032). Adolescents who reported high averages of SMU intensity also reported high averages of SMU problems ($r = 0.40$, $p < 0.001$).

Table 5.5 depicts the auto-regressive and cross-lagged effects at the within-person level. Results for Hypotheses 1 and 2 are denoted by the light gray cells in the table and are all non-significant. Specifically, adolescents whose ADHD-symptoms increased did not report increases in SMU intensity one year later, nor did they report increased SMU problems one year later. These findings refute Hypotheses 1 and 2.

The dark gray cells in Table 5.5 depict results for Hypotheses 3 and 4. Adolescents whose SMU intensity increased did not report increases in ADHD-symptoms one year later, because we did not find cross-lagged effects between SMU intensity and ADHD-symptoms. This finding fails to support Hypothesis 3. However, adolescents whose SMU problems increased, also experienced increased attention deficits one year later, both from T1 to T2 ($\beta = 0.31$, $p = 0.004$) and from T2 to T3 ($\beta = 0.50$, $p = 0.016$). Comparison of unstandardized effect sizes using a Wald-test indicated that the strength of these found relations were not significantly different ($\chi^2(1) = 0.03$, $p = 0.870$). Also, adolescents who experienced increased SMU problems at T2, reported

**Table 5.4**

*RI-CLPM, Between-Person Correlations (n = 543)*

| | SMU intensity | | | SMU problems | | | Attention deficits | | | Impulsivity | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *r* | *SE* | *p* | *r* | *SE* | *p* | *r* | *SE* | *p* | *r* | *SE* | *p* |
| SMU intensity | 1.00 | | | | | | | | | | | |
| SMU problems | 0.40 | 0.08 | < 0.001 | 1.00 | | | | | | | | |
| Attention deficit | 0.23 | 0.06 | < 0.001 | 0.24 | 0.11 | 0.032 | 1.00 | | | | | |
| Impulsivity | 0.23 | 0.06 | < 0.001 | 0.23 | 0.11 | 0.031 | 0.67 | 0.05 | < 0.001 | 1.00 | | |
| Hyperactivity | 0.29 | 0.06 | < 0.001 | 0.29 | 0.10 | 0.003 | 0.63 | 0.07 | < 0.001 | 0.64 | 0.05 | < 0.001 |

*Notes.* SMU = social media use; RI-CLPM = random intercept cross-lagged panel model; *r* = correlation; *SE* = standard error; *p* = p-value.

**Table 5.5**

*RI-CLPM, Standardized Within-Person (Cross-)Lagged Effects (n = 543)*

| **(T2 →)** | **SMU intensity** | | | **SMU problems** | | | **Attention deficits** | | | **Impulsivity** | | | **Hyperactivity** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *β* | *SE* | *p* | *β* | *SE* | *p* | *β* | *SE* | *p* | *β* | *SE* | *p* | *β* | *SE* | *p* |
| (T1 ↓) | | | | | | | | | | | | | | | |
| SMU intensity | 0.10 | 0.15 | 0.506 | 0.02 | 0.05 | 0.758 | 0.05 | 0.08 | 0.508 | 0.03 | 0.10 | 0.739 | 0.10 | 0.08 | 0.221 |
| SMU problems | 0.31 | 0.21 | 0.140 | 0.79 | 0.04 | < 0.001 | 0.31 | 0.11 | 0.004 | 0.19 | 0.13 | 0.150 | 0.07 | 0.09 | 0.409 |
| Attention deficit | -0.03 | 0.18 | 0.857 | -0.04 | 0.05 | 0.421 | 0.42 | 0.12 | 0.001 | 0.05 | 0.13 | 0.721 | -0.08 | 0.09 | 0.391 |
| Impulsivity | -0.06 | 0.18 | 0.735 | 0.13 | 0.08 | 0.090 | -0.08 | 0.17 | 0.623 | 0.07 | 0.17 | 0.671 | 0.03 | 0.14 | 0.857 |
| Hyperactivity | 0.14 | 0.16 | 0.380 | -0.04 | 0.04 | 0.413 | -0.06 | 0.12 | 0.611 | 0.19 | 0.11 | 0.094 | 0.53 | 0.10 | < 0.001 |
| **(T3 →)** | **SMU intensity** | | | **SMU problems** | | | **Attention deficits** | | | **Impulsivity** | | | **Hyperactivity** | | |
| | *β* | *SE* | *p* | *β* | *SE* | *p* | *β* | *SE* | *p* | *β* | *SE* | *p* | *β* | *SE* | *p* |
| (T2 ↓) | | | | | | | | | | | | | | | |
| SMU intensity | 0.29 | 0.29 | 0.311 | -0.05 | 0.06 | 0.447 | -0.13 | 0.20 | 0.511 | -0.08 | 0.16 | 0.602 | -0.04 | 0.19 | 0.831 |
| SMU problems | 0.33 | 0.24 | 0.163 | 0.99 | 0.04 | < 0.001 | 0.50 | 0.21 | 0.016 | 0.51 | 0.14 | < 0.001 | 0.28 | 0.20 | 0.158 |
| Attention deficit | -0.26 | 0.22 | 0.248 | -0.01 | 0.05 | 0.910 | 0.19 | 0.24 | 0.431 | -0.19 | 0.18 | 0.281 | -0.26 | 0.22 | 0.241 |
| Impulsivity | 0.13 | 0.17 | 0.450 | -0.05 | 0.04 | 0.294 | 0.19 | 0.15 | 0.191 | 0.38 | 0.14 | 0.008 | 0.14 | 0.16 | 0.382 |
| Hyperactivity | 0.08 | 0.20 | 0.678 | 0.00 | 0.05 | 0.999 | -0.26 | 0.16 | 0.112 | 0.04 | 0.13 | 0.763 | 0.34 | 0.18 | 0.054 |

*Notes.* SMU = social media use; RI-CLPM = random intercept cross-lagged panel model; *β* = standardized coefficient; *SE* = standard error; *p* = p-value. Light gray cells depict results for Hypotheses 1 and 2; Dark gray cells depict results for Hypotheses 3 and 4.

increased impulsivity at T3 ($\beta = 0.51$, $p < 0.001$). The strength of this relation was equal to the relation between SMU problems at T2 and attention deficit at T3 ($\chi^2(1) = 0.41$, $p = 0.522$). However, increased SMU problems at T1 did not increase impulsivity at T2. We also did not find that increased SMU problems increased hyperactivity over time. Considering these results, Hypothesis 4 is partially confirmed.

### Additional Findings

Although adolescents who reported high SMU intensity also reported more SMU problems at the between-person level (Table 5.4), the results in Table 5.5 show that on the within-person level, adolescents whose SMU intensity increased did not report increased SMU problems one year later. Neither did adolescents whose SMU problems increased report increased SMU intensity one year later. In addition, adolescents whose SMU problems increased also reported increased SMU problems one year later, across all waves with relatively large effect sizes (from T1 to T2 $\beta = 0.79$, $p < 0.001$; from T2 to T3 $\beta = 0.99$, $p < 0.001$). This suggests that increased SMU problems were persistent over time. Such a pattern was not observed regarding SMU intensity. Also, adolescents whose attention deficits increased at T1 reported increased attention deficits at T2 ($\beta = 0.42$, $p = 0.001$). Increased hyperactivity at T1 was associated with increased hyperactivity at T2 ($\beta = 0.53$, $p < 0.001$). Increased impulsivity at T2 was associated with increased impulsivity at T3 ($\beta = 0.38$, $p = 0.008$).

In addition, all measures at the within-person level were positively correlated within T1 (Table 5.6). This means that during this wave, increases in SMU intensity, SMU problems, attention deficits, impulsivity, and hyperactivity occurred simultaneously. These associations were also found in T2, with the exception that increases in SMU intensity were not correlated with increases in attention deficits or impulsivity. During T3, increases in SMU intensity were not associated with increases in ADHD-symptoms in the same wave, but SMU problems increased simultaneously with impulsivity.

## Discussion

This study investigated the direction of the relation between ADHD-symptoms and both SMU intensity and SMU problems among adolescents,

**Table 5.6**

*RI-CLPM, (Residual) Correlations Within Waves (n = 543)*

| (T1 →) | SMU intensity | | | SMU problems | | | Attention deficits | | | Impulsivity | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Correlations (T1 ↓)** | ***r*** | ***SE*** | ***p*** | ***r*** | ***SE*** | ***p*** | ***r*** | ***SE*** | ***p*** | ***r*** | ***SE*** | ***p*** |
| SMU intensity | 1.00 | | | | | | | | | | | |
| SMU problems | 0.38 | 0.10 | < 0.001 | 1.00 | | | | | | | | |
| Attention deficit | 0.26 | 0.08 | 0.001 | 0.42 | 0.09 | < 0.001 | 1.00 | | | | | |
| Impulsivity | 0.40 | 0.08 | < 0.001 | 0.55 | 0.10 | < 0.001 | 0.69 | 0.06 | < 0.001 | 1.00 | | |
| Hyperactivity | 0.40 | 0.07 | < 0.001 | 0.31 | 0.10 | 0.002 | 0.50 | 0.08 | < 0.001 | 0.63 | 0.06 | < 0.001 |
| **(T2 →)** | **SMU intensity** | | | **SMU problems** | | | **Attention deficits** | | | **Impulsivity** | | |
| **Residual correlations (T2 ↓)** | ***r*** | ***SE*** | ***p*** | ***r*** | ***SE*** | ***p*** | ***r*** | ***SE*** | ***p*** | ***r*** | ***SE*** | ***p*** |
| SMU intensity | 1.00 | | | | | | | | | | | |
| SMU problems | 0.43 | 0.10 | < 0.001 | 1.00 | | | | | | | | |
| Attention deficit | 0.16 | 0.15 | 0.295 | 0.44 | 0.07 | < 0.001 | 1.00 | | | | | |
| Impulsivity | 0.25 | 0.15 | 0.089 | 0.46 | 0.07 | < 0.001 | 0.64 | 0.07 | < 0.001 | 1.00 | | |
| Hyperactivity | 0.39 | 0.14 | 0.007 | 0.40 | 0.05 | < 0.001 | 0.57 | 0.06 | < 0.001 | 0.53 | 0.07 | < 0.001 |
| **(T3 →)** | **SMU intensity** | | | **SMU problems** | | | **Attention deficits** | | | **Impulsivity** | | |
| **Residual correlations (T3 ↓)** | ***r*** | ***SE*** | ***p*** | ***r*** | ***SE*** | ***p*** | ***r*** | ***SE*** | ***p*** | ***r*** | ***SE*** | ***p*** |
| SMU intensity | 1.00 | | | | | | | | | | | |
| SMU problems | 0.06 | 0.10 | 0.575 | 1.00 | | | | | | | | |
| Attention deficit | -0.11 | 0.19 | 0.574 | 0.12 | 0.11 | 0.256 | 1.00 | | | | | |
| Impulsivity | -0.07 | 0.13 | 0.586 | 0.17 | 0.07 | 0.022 | 0.51 | 0.08 | < 0.001 | 1.00 | | |
| Hyperactivity | -0.11 | 0.16 | 0.491 | 0.02 | 0.09 | 0.793 | 0.31 | 0.15 | 0.048 | 0.34 | 0.11 | < 0.001 |

*Notes*. SMU = social media use; RI-CLPM = random intercept cross-lagged panel model; *r* = correlation; *SE* = standard error; *p* = p-value.

using longitudinal data. Over time, SMU problems, but not SMU intensity, increased ADHD-symptoms. Specifically, we consistently found that adolescents whose SMU problems increased, also experienced increased attention deficits one year later. Adolescents' increased SMU problems at T2 also increased impulsivity at T3. Yet, adolescents whose ADHD-symptoms increased neither reported increased SMU intensity one year later nor did they report increased SMU problems one year later.

The finding that adolescents' SMU problems increased ADHD-symptoms one year later, while SMU intensity did not, provides several insights. First, it suggests that the impact of SMU on ADHD-symptoms was not driven by the frequency of use, but rather by the addiction-like aspect of problematic use, such as constant urge to go online or the inability to control SMU. Second, it supports the idea that SMU problems – as defined by substance dependence criteria – have harmful implications, which has been contested in scholarly debates (Kardefelt-Winther et al., 2017; Van Rooij et al., 2018). Previous longitudinal analyses showed that SMU problems, but not SMU intensity, diminished life satisfaction over time (Van den Eijnden et al., 2018). Extending these findings, the present study suggests that SMU problems also increase ADHD-symptoms, whereas SMU intensity does not. Third, the finding that SMU intensity did not increase ADHD-symptoms over time suggests that intensive use of social media may be a normative behavior that is integrated into adolescents' daily lives rather than a problematic behavior. The additional finding that increased SMU intensity did not precede increased SMU problems one year later supports this idea.

The longitudinal association between SMU problems and ADHD-symptoms was most pronounced from T2 (2016) to T3 (2017), when increases in SMU problems not only predicted increases in attention deficit, but also increases in impulsivity. This may be because social media platforms became more advanced during this period. For example, Instagram – a social network site for sharing photos through a personal profile – was extended in 2016 with the possibility to share 'Stories', which is a series of photos or videos that disappear after 24 hours. Also, Snapchat – a popular instant messenger for sharing photos that disappear after 10 seconds – provided extra incentives for their users from 2016 onwards to use it more intensively, for instance through the launch of 'Snapstreaks', which indicate the number of consecutive days users exchanged photos with particular friends (Werning, 2017). The new affordances may have made social media even more attractive to adolescents and made them harder to resist. These changes may tax adolescents' self-control more heavily, in turn increasing ADHD-symptoms.

We did not find support for our proposition that adolescents with more ADHD-symptoms would be particularly attracted to the features of social media. Although adolescents with more ADHD-symptoms are sensitive to developing addiction-like behaviors, such as substance dependence (Ohlmeier et al., 2008), we did not observe this sensitivity for the development of SMU problems. Social media are possibly more salient in the daily lives of adolescents than substances. Therefore, SMU problems may be different in their etiology from substance dependence. Alternatively, our study design and method might have prevented us from observing an effect of ADHD-symptoms on social media behaviors. Specifically, ADHD-symptoms may have affected social media behaviors at a younger age, not included in our study. Furthermore, the measurement occasions were a year apart, while behaviors may influence each other within a shorter time interval. Also, adolescents' initial level of ADHD-symptoms at the between-person level (e.g., genetically determined) may have influenced changes in social media behaviors. The within-person oriented study design of the RI-CLPM does not eliminate the possibility that stable levels of ADHD-symptoms at the between-person level affected social media behaviors over time.

An additional finding was that adolescents who experienced increased SMU problems were likely to experience increased SMU problems one year later as well, with high effect sizes. Scholars have questioned whether SMU problems, indicated by symptoms of addiction, reflect actual behavioral addiction symptoms. They have put forward that the behavior should lead to significant impairment, and that it should persist over time (Kardefelt-Winther et al., 2017). The finding that SMU problems have harmful implications over time, and that they are highly likely to persist over time, supports the suggestion that SMU problems, as defined in this study, reflect behavioral addiction symptoms.

## Strengths, Limitations and Future Directions

The present study has important strengths related to the research design. By disentangling within- and between-person effects, we controlled for all possible confounding time-invariant traits. The findings of this study are therefore an important first step in answering the question of directionality. By distinguishing two types of social media behaviors and three symptoms of ADHD, we gained a better understanding of the relation between specific elements of both social media behaviors and of ADHD-symptoms. However, the self-report measures used in this study may deviate from observed ADHD- and social media behaviors (Orben & Przybylski, 2019a). Also, due to the use of long time-intervals, potential relations between daily fluctuations in ADHD-symptoms and social media behaviors could not be observed. Additionally, time-varying covariates that are not included in the study may have contributed to the found associations. For example, age may have played a role in the found relations over time, because during adolescence SMU intensity typically increases with age (Boer & Van den Eijnden, 2018). Furthermore, the convenience sample and the somewhat overrepresented native and pre-university adolescents relative to the general adolescent population in the Netherlands limit the generalizability of our findings.

Taking these limitations into account, more longitudinal research on social media behaviors and ADHD-symptoms using more waves and shorter time-intervals, with larger and more representative samples is desired to confirm the unidirectional conclusion of the present study. More specifically, future research using smartphone applications that measure time spent on (specific) social media in combination with momentary assessments of ADHD-symptoms may provide more objective (and specific) insights into the relation between SMU intensity and ADHD-symptoms over time (Orben & Przybylski, 2019a). Another promising direction for future research would be the investigation of the longitudinal relations between social media behaviors and ADHD-symptoms for different subgroups separately, because particular groups (e.g., girls, low-educated) may be more susceptible to media effects (Valkenburg & Peter, 2013).

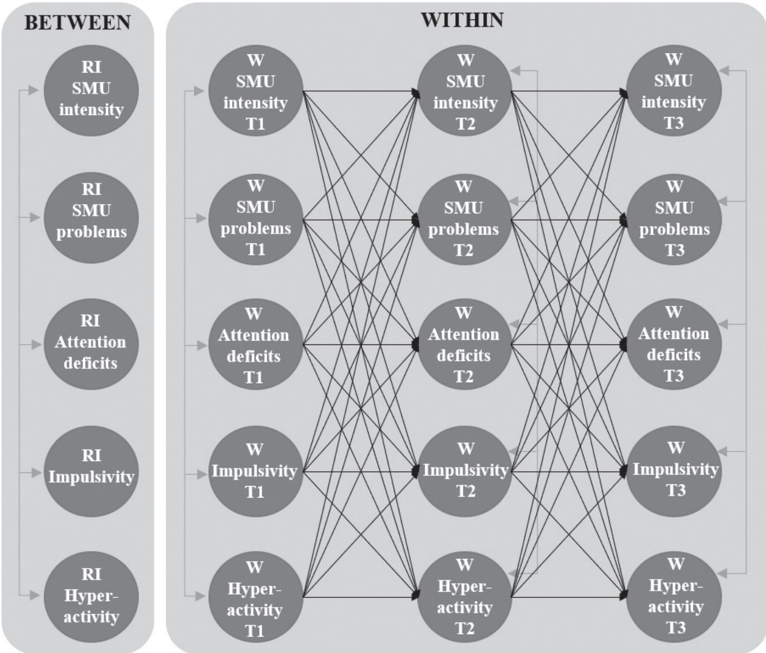
## Conclusion

To conclude, findings from this longitudinal study suggest that SMU problems increase ADHD-symptoms among adolescents, but SMU intensity does not. Moreover, our findings indicate that the relation was unidirectional, because the reverse pattern was not observed. The present study extends current knowledge obtained from cross-sectional research, and highlights the importance of distinguishing SMU problems from SMU intensity in understanding the relation between ADHD-symptoms and social media behaviors. While SMU intensity may not be harmful, SMU problems need to be recognized as harmful to adolescent mental health.

# Appendix

**Figure A5.1**

*Simplified Illustration of the Five-Variable Random Intercept Cross-Lagged Panel Model*




*Notes.* Circles in the between-area represent random intercepts (RI), which were extracted from their three respective computed factor scores (not shown in figure). Circles in the within-area represent within-person values (W), which were extracted from their respective computed factor score (not shown in figure). Black arrows represent cross-lagged and auto-regressive relations. All possible cross-lagged relations were specified for control purposes (e.g., attention deficits at T1 on impulsivity at T2). Light gray arrows represent (residual) correlations.

# CHAPTER 6

# SOCIAL MEDIA USE INTENSITY, SOCIAL MEDIA USE PROBLEMS, AND MENTAL HEALTH AMONG ADOLESCENTS: INVESTIGATING DIRECTIONALITY AND MEDIATING PROCESSES

Maartje Boer, Gonneke W. J. M. Stevens, Catrin Finkenauer, Margaretha E. de Looze, and Regina J. J. M. van den Eijnden

**Author Contributions**

All authors conceived of the study. MB conducted the literature review, data analyses, and drafted the initial and revised manuscript. RvdE initiated and coordinated the data collection of the data from the present study. GS, CF, MdL, and RvdE critically reviewed all sections of the initial and revised manuscript and advised during all stages of the manuscript preparation. All authors approved of the final manuscript.

**Publication**

Boer, M., Stevens, G. W. J. M., Finkenauer, C., De Looze, M. E., & Van den Eijnden, R. J. J. M. (2021). Social media use intensity, social media use problems, and mental health among adolescents: Investigating directionality and mediating processes. *Computers in Human Behavior*, *116*, 106645. https://doi.org/10.1016/j.chb.2020.106645

# Abstract

Social media have become increasingly integrated into the daily lives of adolescents. There are concerns about the potential detrimental effects of adolescents' social media use (SMU) on their mental health. Using a three-wave longitudinal study among 2,109 secondary school adolescents ($M_{age}$ = 13.1, $SD_{age}$ = 0.8), the present study examined whether high SMU intensity and addiction-like SMU problems were bidirectionally associated with low mental health, and whether these associations were mediated by increased levels of upward social comparisons, cybervictimization, decreased subjective school achievements, and less face-to-face contact with friends. In doing so, mental health was measured by depressive symptoms and life satisfaction. Findings from random intercept cross-lagged panel models showed a direct unidirectional association between SMU problems and mental health: SMU problems were associated with decreased mental health one year later, but not vice versa. SMU problems also predicted increased levels of upward social comparisons and cybervictimization one year later. Yet, these processes did not mediate the observed effect of SMU problems on decreased mental health. Over time, SMU intensity and mental health were not associated in any direction, neither directly, nor indirectly through any of the mediators. Findings of our study suggest that harmful effects of SMU intensity may be limited and highlight the potential risk of SMU problems to adolescent mental health.


*Keywords*: social media use, problematic social media use, social media addiction, mental health, adolescents.

# Social Media Use Intensity, Social Media Use Problems, and Mental Health among Adolescents: Investigating Directionality and Mediating Processes

Social media, such as Instagram and Snapchat, are immensely popular among adolescents (Anderson & Jiang, 2018; Vannucci & McCauley Ohannessian, 2019). Concerns have been raised about adolescents' social media use (SMU) and its impact on their mental health, in particular on their life satisfaction and depressive symptoms (Primack & Escobar-Viera, 2017; Underwood & Ehrenreich, 2017). The present study investigated the relationship between SMU and mental health in adolescents. In doing so, we distinguished *SMU intensity* from *SMU problems* as two separate dimensions of SMU. SMU intensity refers to the frequency of SMU, whereas SMU problems indicate addiction-like SMU, such as loss of control over SMU or neglecting hobbies or other activities due to SMU (Van den Eijnden et al., 2016). Although adolescents with SMU problems tend to also display high SMU intensity, high SMU intensity does not necessarily imply loss of control over SMU or interference with important life domains. Yet, research suggests that both types of SMU are negatively related to adolescents' mental health, including their life satisfaction, happiness, and other emotional problems (Mérelle et al., 2017; Twenge, Martin, et al., 2018). Given that SMU intensity and SMU problems differ conceptually, they may have differential associations with mental health. However, research that investigates this hypothesis is scarce. Also, we know little about the directionality of these associations and their underlying processes. Using three waves of longitudinal data among adolescents, the present study addressed these gaps in the literature by investigating bidirectional associations between both types of SMU and mental health, and possible mediators in these associations. The study thereby aims to advance current knowledge on the potential link between social media behaviors and mental health, which is essential given the prominent role social media play into the daily lives of adolescents.

## SMU Intensity and Mental Health

Cross-sectional research suggests that adolescents' SMU intensity is associated with lower life satisfaction and more depressive symptoms, although the strength of these associations was often small (Kelly et al., 2018; Twenge, Joiner, et al., 2018; Twenge, Martin, et al., 2018). Researchers argue that this link could be bidirectional: On the one hand, adolescents who use social media intensively may be sensitive to mental health problems because they spend less time on offline activities that are important to their mental health (Primack & Escobar-Viera, 2017; Underwood & Ehrenreich, 2017). On the other hand, adolescents with more mental health problems may be more inclined to use social media more intensively to find emotional and social support for their problems (Radovic et al., 2017). Some longitudinal studies support these propositions (Frison & Eggermont, 2017; Heffer et al., 2019; Riehm et al., 2019), whereas others found no or only a very small bidirectional association between SMU intensity and mental health (Coyne et al., 2020; Houghton et al., 2018; Orben et al., 2019). The few studies that examined both adolescents' SMU intensity and SMU problems and their associations with mental health in one model repeatedly showed that SMU intensity was not or only weakly associated with lower mental health, whereas SMU problems were consistently related to lower mental health (Boer, Van den Eijnden, et al., 2020; Shensa et al., 2017; Van den Eijnden et al., 2018). These findings imply that previously found negative associations between high SMU intensity and mental health were possibly driven by a confounding effect of SMU problems.

High SMU intensity may not necessarily harm mental health, because frequent SMU may not interfere with life domains that are relevant to adolescents' mental health, such as offline socializing with friends or family (Boer, Van den Eijnden, et al., 2020). Hence, adolescents who engage in high SMU intensity may be well able to regulate their SMU and to combine it with a healthy lifestyle. Reversely, low mental health may not increase SMU intensity because nowadays, many adolescents use social media intensively to maintain and enhance their social involvement with peers (Anderson & Jiang, 2018; Boyd, 2014; Vannucci & McCauley Ohannessian, 2019). Therefore, high SMU intensity may rather be normative adolescent behavior than behavior that is specific to adolescents with low mental health. Accordingly, we expected that high SMU intensity would not be associated with mental health in any direction.

## SMU Problems and Mental Health

In contrast, cross-sectional studies repeatedly showed that adolescents with SMU problems report mental health problems, such as depressive symptoms and other emotional problems, with moderate to large effect sizes (Bányai et al., 2017; Mérelle et al., 2017; Pontes, 2017). However, it is unclear whether SMU problems precede or follow from poor mental health. The presence of SMU problems may lead to lower mental health, because, as compared to adolescents who solely show high SMU intensity by using social media very frequently, adolescents with SMU problems show addiction-like SMU. That is, adolescents with SMU problems often have a diminished ability to regulate their SMU impulses, perceive SMU as more important than other activities, are preoccupied with social media, feel a constant urge to go online, and/or experience discomfort such as stress or anxiety when SMU is not possible (Apaolaza et al., 2019; Griffiths, 2013; Griffiths et al., 2014). In other words, they have diminished control over their thoughts, emotions, and behaviors, and social media dominates their daily lives. This loss of agency, that is typical to SMU problems, may harm adolescents' mental health. Therefore, we expected that SMU problems would decrease mental health.

Reversely, low mental health may also elicit SMU problems. The *cognitive behavioral model* posits that pre-existing psychopathology, such as depression, drive maladaptive cognitions about social media (Caplan, 2003; Davis, 2001; Griffiths, 2013). Adolescents with such cognitions may feel, for example, that their offline life is less meaningful than their online life, or that SMU alleviates their sorrows (Davis, 2001). To feel positive about themselves, or to forget their problems, they may become dependent on SMU, and therefore develop addiction-like SMU problems (Griffiths, 2013). Thus, we also expected that poorer mental health would increase SMU problems.

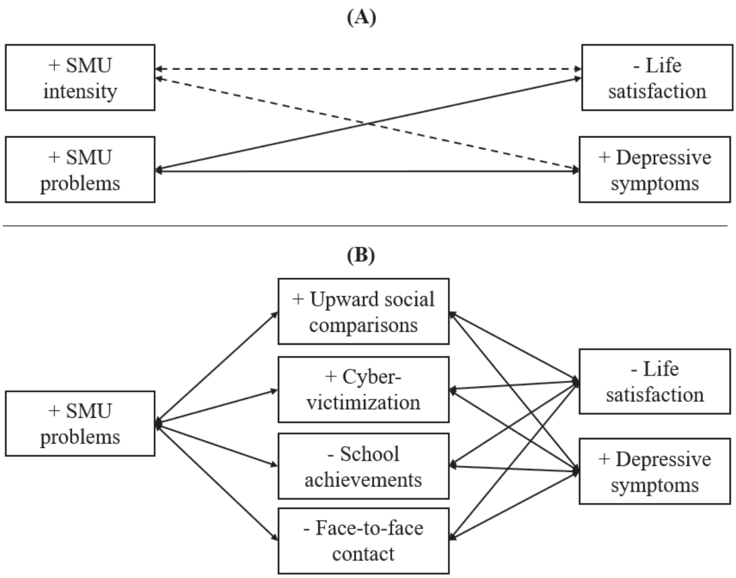
## Mediating Processes

The proposed bidirectional pathways between SMU problems and mental health may be driven by several underlying behaviors (Marino et al., 2018b, 2018a), yet these have received little empirical attention. The present study considers four mediating processes that could explain the effect of SMU problems on low mental health (Figure 6.1). First, adolescents with SMU problems typically attach excessive importance to social media, and may therefore perceive the online world, which is heavily biased toward idealist self-presentations, as social reality. They may therefore not be able to place the overly flattered portrayals of others into perspective. As a result, they may engage in *upward social comparisons*. That is, they may perceive their peers' appearances as superior to their own (Pera, 2018). Second, driven by their cravings for the potential social reward afforded by SMU, such as the reassurance to be noticed and appreciated by others (Veissière & Stendel, 2018), adolescents with SMU problems may engage in high levels of self-disclosure on social media (Blau, 2011). This, in turn, may make them vulnerable to *cybervictimization* (Weber et al., 2013). Finally, given that adolescents with SMU problems typically perceive SMU as their most important activity and that abstaining from it may cause stress or anxiety, they may displace offline social activities with peers and schoolwork activities with SMU. This may, third and fourth, go at the expense of *face-to-face contact* and *school achievement* (Salmela-Aro et al., 2017; Underwood & Ehrenreich, 2017; Wallsten, 2013). These four adverse processes, that may result from SMU problems, in turn, may decrease mental health. Accordingly, we expected that SMU problems would decrease mental health through upward social comparisons, cybervictimization, decreased face-to-face-contact, and decreased school achievements.

These four processes may also underlie the reverse proposed effect, that is, the effect of lower mental health on SMU problems (Figure 6.1). First, the negative self-perceptions that adolescents with poorer mental health typically have may reinforce upward social comparisons after exposure to their peers' idealized appearances on social media (Nesi et al., 2017). Second, adolescents with mental health impairments may face a higher risk of cybervictimization, as their vulnerabilities may make them an easy target for aggressive peers (C. A. Rose & Tynes, 2015; Van den Eijnden et al., 2014), Third, they may also have less face-to-face contact with peers, because peers may perceive them as less attractive to be friends with (Connolly et al., 1992). Fourth, poor mental health may also be a source of decreased schoolwork achievements (Brännlund et al., 2017). In order to compensate and/or find relief for these additional adversities, that may stem from poor mental health, adolescents may become more dependent upon and preoccupied with SMU. This maladaptive coping strategy may ultimately elicit SMU problems (Griffiths et al., 2014). We therefore expected that poorer mental health would increase SMU problems through upward social comparisons, cybervictimization, decreased face-to-face-contact, and decreased school achievements.

**Figure 6.1**

*Path Diagram of Hypothesized Direct and Indirect Associations*




*Notes.* The double-headed arrows denote that associations were examined bidirectionally. Solid arrows indicate the expected significant associations. Dashed arrows indicate that no associations were expected. Diagram A displays the hypothesized direct effects. Diagram B displays the hypothesized mediations.



## Current Study

Using three waves of longitudinal data among Dutch adolescents in their first two years of secondary school, the present study examined bidirectional associations between adolescents' SMU intensity as well as SMU problems and mental health. In this study, mental health was defined by the presence of wellbeing as well as the absence of mental illnesses (Herrman et al., 2005). We therefore focused on two aspects of mental health: the presence of life satisfaction and the absence of depressive symptoms. Based on recent findings that refute the alleged negative link between SMU intensity and mental health and because high SMU intensity is considered normative in adolescence, we expected that SMU intensity would be unrelated to mental health in any direction; neither directly nor indirectly. Rather, we expected that addiction-like SMU problems would decrease mental health. We also expected, reversely, that poor mental health would increase SMU problems. We also examined whether these proposed bidirectional associations were mediated by upward social comparisons, cybervictimization, decreased face-to-face contact with peers, and worsened school achievements (Figure 6.1).

# Methods

## Sample

Data were obtained from the Digital Youth-project: a self-report longitudinal study on online behaviors and mental health among Dutch secondary school students (Van den Eijnden et al., 2018). We used data from the second, third, and fourth wave, which took place in February and March of 2016, 2017, and 2018, respectively. Data from the first wave were excluded because depressive symptoms were not measured in this wave. The waves that were included in the current study are further referred to as T1, T2, and T3. In order to study developments of adolescents from a similar age category, we selected students who were in the first two school years of secondary school at T1 ($n$ = 2,228). Students for whom data were missing on all study measures were excluded from the sample, which yielded a final analysis sample of 2,109 adolescents from 9 schools. From this sample, 77.9% participated in T1, 75.0% participated in T2, and 40.5% participated in T3. The nonresponse was mainly due to dropout of schools and classes, because teachers were absent or not able to schedule the survey assessments at participating schools. Hence, we considered the dropout as not selective.

At T1, participating students from the analysis sample were between 10 and 16 years old ($M$ = 13.1, $SD$ = 0.8) and 43.1% were first year students. In addition, 43.1% were girls, 25.7% had an immigrant background, and students were attending education at different levels (65.3% pre-vocational, 24.2% intermediate, and 10.5% pre-university). Girls and students with pre-university education were somewhat underrepresented compared to the Dutch adolescent population of the same age category in 2017 (49.1% girl, 51.1% pre-vocational, 22.1% intermediate, and 21.6% pre-university) (Central Bureau for Statistics, 2019a). Sample characteristics in T2 were approximately the same as in T1 (45.0% girls, 23.7% immigrant background, 62.5% pre-vocational, 26.2% intermediate, and 11.3% pre-university). In T3, two pre-vocational level schools dropped out due to practical circumstances, as well as several pre-vocational level classes from the other schools, which yielded a different sample composition compared to T1 and T2 (43.9% girls, 17.6% immigrant background, 33.8% pre-vocational, 44.6% intermediate, and 21.6% pre-university).

Two weeks prior to the survey assessment, information letters were sent to parents to provide information about the survey and to allow parents to refuse participation of their child. One week prior to the survey assessment, students were informed about the subject and purposes of the study, that participation was voluntary and anonymous, and that they could resign participation at any moment. Students completed the online survey during school hours. Research-assistants monitored students' survey completion and provided help where necessary. The study procedures adhered to the Declaration of Helsinki and were approved by the ethical board of the Faculty of Social Sciences at Utrecht University (FETC16-076 Eijnden).



## Measures

### *SMU Problems*

SMU problems were measured using the 9-item Social Media Disorder-Scale, that assesses nine symptoms of addiction to social media (Van den Eijnden et al., 2016). Respondents were asked 'During the past year, have you …', followed by 'regularly found that you can't think of anything else but the moment that you will be able to use social media again' (preoccupation), 'regularly felt dissatisfied because you wanted to spend more time on social media' (tolerance), 'often felt bad when you could not use social media' (withdrawal), 'been unable to stop using social media, even though others told you that you really should' (persistence), 'regularly had no interest in hobbies or other activities because you would rather use social media' (displacement), 'regularly had arguments with others because of your social media use' (problem), 'often used social media secretly' (deception), 'often used social media so you didn't have to think about unpleasant things' (escape), and 'had serious conflict with your parent(s) and sibling(s) because of your social media use (conflict), with a dichotomous response scale (*yes* or *no*). The scale has been found to have solid structural and criterion validity and good reliability among adolescents (Boer, Stevens, Finkenauer, Koning, et al., 2021). Due to the dichotomous nature of the items, internal consistency was calculated using the tetrachoric correlation matrix (Gadermann et al., 2012). This yielded an ordinal alpha that varied between 0.83 and 0.85 at the different waves.

### *SMU Intensity*

Four items assessed respondents' SMU intensity (Boer, Stevens, et al., 2020), which measured the frequency of different social media activities. The first three items examined 'How many times *per day* do you view social network sites', 'How many times *per week* do you 'like' messages, photos, or videos of others on social network sites', and 'How many times *per week* do you respond to messages, photos, or videos of others on social network sites' (1 *never or less than once* to 7 *more than 40 times*). The questionnaire provided examples of social network sites ('for example Facebook, Twitter, Instagram, Google+, or Pinterest, but not WhatsApp or SnapChat'). The fourth item examined 'How many times *per day* do you send a message, photo or video via your smartphone, for example a WhatsApp, Chat, SnapChat, or SMS' (1 *less than once* to 7 *more than 80 times*). Cronbach's alpha varied between 0.78 and 0.84 across waves. The original scale consisted of two additional items: 'How many times *per week* do you post a message, photo, or video on social network sites' and 'How many times *per day* do you check your smartphone to see whether you have received a message, photo, or video, for example a WhatsApp, Chat, SnapChat, or SMS?'. The first item of these two was excluded because its factor loading was low (< 0.5). The second item was excluded because it showed relatively high overlap with the other item on smartphone use ($r$ = 0.7), and therefore removing the item yielded substantial model fit improvement (Boer, Stevens, et al., 2020).

### *Depressive Symptoms*

Respondents reported on their depressive symptoms using the 6-item Depressive Mood List (Kandel & Davies, 1982). They indicated, for example, how often in the past year they were 'Feeling too tired to do things', 'Feeling unhappy, sad, or depressed', 'Having trouble going to sleep or staying asleep', 'Feeling hopeless about the future', 'Feeling nervous or tense', and 'Worrying too much about things' (1 *never* to 5 *always*). The scale has been validated among U.S. secondary school students but has been adopted extensively in adolescent surveys (Compas et al., 1993), also in translated form among Dutch adolescents (Engels et al., 2001; Van Rooij et al., 2014). The scale has been found to have appropriate internal consistency and test-retest reliability (Compas et al., 1993). In the present sample, Cronbach's alpha varied between 0.81 and 0.87 in all waves.

***Life Satisfaction***

Respondents indicated their life satisfaction using the 7-item Student's Life Satisfaction Scale (Huebner, 1991). Respondents were asked about their thoughts around their own life: 'My life is going well', 'My life is just right', 'I would like to change many things in my life', 'I wish I had a different kind of life', 'I have a good life', 'I have what I want in life', and 'My life is better than most kids' (1 *strongly disagree* to 6 *strongly agree*). The third and fourth item were recoded such that higher values indicated higher life satisfaction. The scale has been validated extensively among elementary and secondary school U.S. students and showed adequate convergent and discriminant validity and test-retest reliability (Huebner, 2004). The scale has been translated and adopted across many countries (Proctor et al., 2009). In the present study, Cronbach's alpha varied between 0.83 and 0.84 in all waves.



***Upward Social Comparisons***

A newly developed 5-item scale measured the extent to which respondents engage in upward social comparison during their SMU. This scale was developed because existing validated measures on social comparison typically assess respondents' overall tendency to compare themselves to others (i.e., not specifically as a result of viewing social media). Respondents indicated, when viewing their peers' messages, photos, or movies on social network sites, how often they thought 'He or she does more fun things than I do', 'He or she has more friends than I do', 'He or she is more popular dan me', 'He or she received more 'likes' than me', and 'He or she looks better than I do' (1 *never* to 5 *very often*). Cronbach's alpha was 0.88 in all three waves.

### *Cybervictimization*

The 10-item Multidimensional Online Peer Victimization Scale was used to assess respondents' level of online peer victimization (Sumter et al., 2015). Respondents indicated how often in the past six months a peer had 'Called me names', 'Insulted me', 'Send me aggressive messages', 'Send me nasty messages', 'Embarrassed me', 'Told my secrets to others so that others do not like me anymore', 'Excluded me from something I wanted to participate in', 'Did not let me join a conversation or chat while I wanted to', 'Purposely acted like I did not exist', and 'Did not let me participate in something I wanted to do' (1 *never* to 6 *about every day*). Cronbach's alpha varied between 0.89 and 0.91 across all waves.

### *Subjective School Achievements*

Three items assessed respondents' subjective school achievements. Respondents were asked 'How satisfied were you with the grades in your most recent school report?' (1 *not satisfied at all* to 5 *very satisfied*), 'How many failing grades did you have in your most recent school report?' (1 *none* to 5 *four or more*), and 'As compared to most of my classmates, I achieve ... school grades' (1 *much worse* to 5 *much better*). The second item was recoded such that high values indicated high school achievement. Cronbach's alpha varied between 0.79 and 0.81 in all the waves. Across all waves, adolescents' mean scores on the three items correlated strongly with their Grade Point Average (GPA)-scores that were obtained from teachers of the participating schools ($r$ = 0.63 to 0.69, $p < 0.001$), which suggests that adolescents' subjective school achievements show high overlap with their objective school achievements. We selected subjective school achievements for this study, as there were relatively many missing values on the GPA-data.

### *Face-to-Face Contact With Friends*

Respondents reported on their intensity of face-to-face contact with friends using three items on the frequency of peer contact (Baams et al., 2017). Respondents were asked 'How often do you spend time with friends after school or in the weekends?', 'How often are you at your friends' house?', and 'How often do you go out at night or go to a party with friends?'. In order to extend the measurement, a fourth item was added to the scale, including 'How often are your friends at your home?' (1 *never* to 6 *very often*). Cronbach's alpha varied between 0.85 and 0.87 across the waves.

## Preliminary Analyses

Prior to our main analyses, we conducted three preliminary analyses using Mplus 8.4 (L. K. Muthén & Muthén, 2017b).

### *Attrition Analyses*

First, we carried out attrition analyses by predicting dropout in T2 and T3 with the study measures at the previous wave using multivariate logistic regressions with the measures modelled as latent variables. Results showed that adolescents with higher levels of SMU problems, lower life satisfaction, lower upward social comparisons, less face-to-face contact, or lower school achievements in T1 were more likely to drop out in T2 ($OR_{range}$ = 1.166 to 1.408). Adolescents with higher levels of SMU problems, higher SMU intensity, higher levels of cybervictimization, or lower levels of upward social comparisons in T2 were more likely to drop out in T3 ($OR_{range}$ = 1.115 to 1.626). The magnitudes of these associations varied from very small ($OR < 1.5$) to small ($OR < 2$) (Sullivan & Feinn, 2012). Thus, although there were relatively many pre-vocational level educated adolescents that dropped out (particularly in T3), associations between our study variables and dropout were limited.

### *Measurement Invariance*

Second, we conducted measurement invariance analysis, because in order to draw valid conclusions about changes over time, our measures should have the same measurement properties across the investigated years (F. F. Chen, 2007; Cheung & Rensvold, 2002). Hence, we examined whether the magnitudes of the item factor loadings and intercepts (or thresholds in case of categorical items) were consistent over time. Measurement invariance was established when applying equality constraints to the item factor loadings and intercepts (or thresholds) did not substantially deteriorate model fit in terms of change in Comparative Fit Index ($\Delta$CFI = decrease of ≤ .010) and Root Mean Square Error of Approximation ($\Delta$RMSEA = increase of ≤ .015;

Chen, 2007). In case equality constraints deteriorated model fit, modification indices were consulted to find the source of misfit. For all measures, applying equality constraints to the factor loadings did not deteriorate model fit, which suggests that all measures had invariant factor loadings over time. Four out of eight measures had one intercept that was not invariant over time. However, each measure had at least two items where the item intercepts were equal over time, which is sufficient for the purpose of our study, namely comparing effect sizes and latent means over time (Van de Schoot et al., 2012).

### *Plausible Values*

Third, we calculated *plausible values* for our measures, which are imputed values that represent the values of latent variables based on a specified factor model using Bayes estimation (Asparouhov & Muthén, 2010c). We followed this method because due to the complexity of our main analyses, it was not feasible to use latent variables in our models. In addition, due to the highly skewed distribution of the sum-score of SMU problems it was not possible to use item sum-scores. Plausible values have been found to accurately resemble covariances between latent variables (Asparouhov & Muthén, 2010c), and as such have been used by researchers to obtain reliable scores for their measures that can be used for subsequent analyses (Ciarrochi et al., 2016; Deutsch et al., 2014; Rhee et al., 2013). For each latent variable, we imputed 20 plausible values based on the factor models as established in our measurement invariance analyses. That is, item factor loadings and intercepts (or thresholds) for which measurement invariance was established were constrained to be equal over time.

Our data were not completely missing at random, as the attrition analysis showed that there were small relationships between the observed data and dropout. In that case, retention of dropout cases provides more reliable model estimates than listwise deletion of dropout cases, especially when dropout rates are high (Enders & Bandalos, 2001). Hence, plausible values for complete as well as dropout cases were estimated with a full information approach (Asparouhov & Muthén, 2010a). That is, plausible values of dropout cases could be estimated based on available data from previous and/or subsequent waves. As a result, all respondents ($n$ = 2,109) were retained in our analyses. All imputations were merged into one dataset for subsequent analyses. Table 6.1 shows the descriptive statistics of the plausible values over the imputed datasets in long format. The plausible values were used for our main analyses.

**Table 6.1**

*Descriptive Statistics (Long Format, n = 6,327)*

| Variable | Mean | *SD* | Min. | Max. |
|---|---|---|---|---|
| SMU problems | -0.013 | 0.663 | -2.411 | 2.530 |
| SMU intensity | 0.120 | 1.278 | -4.470 | 4.176 |
| Depressive symptoms | 0.089 | 0.618 | -1.890 | 2.554 |
| Life satisfaction | -0.212 | 1.044 | -4.723 | 3.069 |
| Upward social comparison | 0.006 | 0.645 | -2.121 | 2.604 |
| Face-to-face contact with friends | -0.042 | 1.042 | -3.712 | 3.533 |
| School satisfaction | -0.006 | 0.946 | -3.508 | 3.240 |
| Cybervictimization | 0.030 | 1.003 | -3.340 | 6.405 |

*Notes.* SD = standard deviation; Min. = minimum; Max. = maximum. Results denote the descriptive statistics of the computed plausible values averaged over 20 imputed datasets. Descriptive statistics were computed with data structured in long format (i.e. each row in the dataset represents an observation).

6

# Main Analyses

### *Analytical Approach*

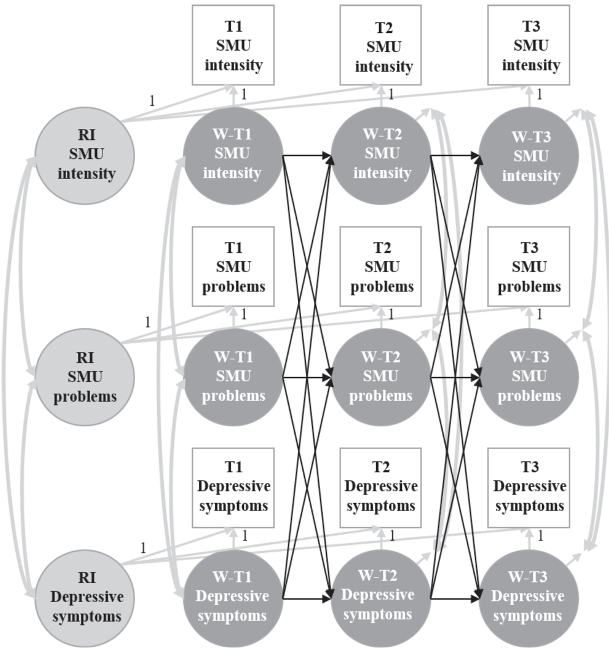
Directionality can be established by studying whether adolescents' increases in, for example, SMU problems precede or follow from increases in, for example, depressive symptoms. Grasping such dynamic processes that occur within adolescents requires separating within-person variance from between-person variance. Hence, we investigated our research questions using the 'random intercept cross-lagged panel model' (RI-CLPM), which is an innovative modelling technique that examines bidirectional processes within persons (Hamaker et al., 2015). By disentangling within- and between-person variance, the RI-CLPM controls for all possible stable characteristics, providing more accurate estimates of directionality (Hamaker et al., 2015).

### *Modelling the RI-CLPM*

Figure 6.2 illustrates a RI-CLPM with SMU intensity, SMU problems, and depressive symptoms. The *between-person part* of the model consisted of the random intercepts (light gray circles), which are latent variables that denote the time-invariant levels of the respective behaviors. The random intercepts were extracted from three repeated plausible values (white squares), with factor loadings constrained to one. The RI-CLPM also included correlations

**Figure 6.2**

*Random Intercept Cross-Lagged Panel Model (RI-CLPM)*




*Notes.* White squares denote plausible values at three measurement occasions ($T_x$). Light gray circles denote the between-level part of the model: the random intercepts (RIs). Correlations between the RIs were specified (gray double arrows). Dark grey circles denote the within-level part of the model: the within-person values (W). Correlations between the within-person values from the same measurement occasion were specified (gray double arrows). Diagonal black arrows depict the cross-lagged paths. Horizontal black arrows depict the auto-regression paths.

between the random intercepts (grey double arrows). The *within-person part* of the model is denoted by the within-person values (dark gray circles), which are latent variables that are extracted from their respective plausible value, each with factor loading constrained to one. The residual variances of the plausible values were constrained to zero. Due to this model specification, the within-person values indicate adolescents' deviations from their time-invariant scores. Hence, positive cross-lagged paths (diagonal black arrows) indicate, for example, whether adolescents who reported increased SMU problems relative to their usual level of SMU problems at T1 reported increased depressive symptoms relative to their usual level of depressive symptoms at T2. By including auto-regressive paths (horizontal black arrows), the cross-lagged paths were controlled for preceding increases (or decreases) of the behaviors. By including correlations between within-person values in the same year (gray double arrows), the cross-lagged paths were also controlled for associated increases (or decreases) in behaviors within the same year. All RI-CLPMs were estimated using Maximum Likelihood with Robust standard errors (MLR).

***Modelling Procedure***

In our first model, we fitted a RI-CLPM with three repeated measures of SMU intensity, SMU problems, and depressive symptoms (M1a). In our second model, we estimated the first model but with life satisfaction instead of depressive symptoms (M2a). We examined depressive symptoms and life satisfaction in separate models due to their collinearity. In subsequent models, we extended the first and second model with the four mediators, with one mediator per model (M1b-e and M2b-e). Model fit was evaluated using the Comparative Fit Index (CFI), Tucker Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and the Standardized Root Mean square Residual (SRMR). The standardized results (STDYX) of the models were used for the interpretation of the effect sizes. Analyses were conducted using Mplus 8.4 (L. K. Muthén & Muthén, 2017b).



# Results

## Descriptive Analyses

Prior to the main analyses, we studied whether adolescents' scores on the study measures changed over time and associations between the demographic characteristics and the study measures using multilevel analysis on the data in long format (Table 6.2). On average, adolescents' SMU problems did not change over time. Relative to T1, adolescents' SMU intensity increased in T2 and T3. In addition, adolescents reported increased depressive symptoms and decreased life satisfaction in T2 and T3 when compared to T1. Also, adolescents reported decreased face-to-face contact in T2 and T3 relative to T1. On average, upward social comparisons, cybervictimization, and subjective school achievements did not change over time. Although on average some measures did not change over time, the within-person residual variances of all measures were significant. This suggests that adolescents

**Table 6.2**

*Descriptive Analyses ($n_{observations}$ = 6,327, $n_{individuals}$ = 2,109)*

| | SMU problems | SMU intensity | Depressive symptoms | Life satisfaction | Upward social comparisons | Cyber-victimizaton | Subjective school achievements | Face-to-face-contact |
|---|---|---|---|---|---|---|---|---|
| ***Level 1 (observations)*** | ***β (SE)*** | ***β (SE)*** | ***β (SE)*** | ***β (SE)*** | ***β (SE)*** | ***β (SE)*** | ***β (SE)*** | ***β (SE)*** |
| T2 (ref.: T1) | -0.053 (0.063) | 0.309*** (0.053) | 0.200*** (0.037) | -0.332*** (0.039) | -0.020 (0.043) | 0.062 (0.038) | -0.014 (0.050) | -0.092* (0.044) |
| T3 (ref.: T1) | -0.106 (0.099) | 0.324*** (0.075) | 0.503*** (0.061) | -0.519*** (0.051) | 0.090 (0.071) | 0.056 (0.051) | 0.011 (0.046) | -0.156** (0.049) |
| ***Level 2 (adolescents)*** | ***β (SE)*** | ***β (SE)*** | ***β (SE)*** | ***β (SE)*** | ***β (SE)*** | ***β (SE)*** | ***β (SE)*** | ***β (SE)*** |
| Girl[1] (ref.: boy) | 0.163** (0.060) | 0.418*** (0.048) | 0.439*** (0.052) | -0.119* (0.055) | 0.382*** (0.055) | -0.159** (0.058) | 0.122 (0.063) | 0.217*** (0.052) |
| Pre-vocational educational level[2] (ref.: pre-university educational level) | 0.431*** (0.091) | 0.396*** (0.081) | -0.076 (0.085) | -0.170 (0.087) | -0.254* (0.098) | 0.328*** (0.080) | -0.496*** (0.107) | 0.426*** (0.073) |
| Intermediate educational level[2] (ref.: pre-university educational level) | 0.199* (0.098) | 0.131 (0.091) | 0.130 (0.088) | -0.169 (0.095) | -0.141 (0.105) | 0.197* (0.090) | -0.480*** (0.113) | 0.223** (0.080) |
| Immigrant background[3] (ref.: native) | 0.073 (0.059) | -0.070 (0.057) | -0.114 (0.059) | 0.015 (0.067) | -0.036 (0.065) | -0.048 (0.065) | -0.162* (0.074) | -0.275*** (0.062) |
| ***Random parameters*** | **Estimate (*SE*)** | **Estimate (*SE*)** | **Estimate (*SE*)** | **Estimate (*SE*)** | **Estimate (*SE*)** | **Estimate (*SE*)** | **Estimate (*SE*)** | **Estimate (*SE*)** |
| Residual variance within adolescents | 0.134*** (0.021) | 0.422*** (0.029) | 0.147*** (0.013) | 0.545*** (0.019) | 0.212*** (0.009) | 0.551*** (0.038) | 0.579*** (0.028) | 0.435*** (0.024) |
| Residual variance between adolescents | 0.296*** (0.042) | 1.131*** (0.068) | 0.214*** (0.020) | 0.515*** (0.036) | 0.194*** (0.013) | 0.438*** (0.037) | 0.305*** (0.029) | 0.624*** (0.036) |

*Notes.* **β** = STDY-standardized, because all covariates were binary; SE = standard error; Ref. = reference category. The models were examined with multivariate multilevel regression analyses (level 1 = observations, level 2 = individuals) using the 20 imputed datasets of plausible values. The models were estimated with Maximum Likelihood with robust standard errors.

[1] Based on question whether respondent was a boy or a girl.

[2] Based on question which level of education the respondent was following. Educational level was determined using the most recent reported educational level.

[3] Based on question in which country parent(s) were born.

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

reported differential developmental trajectories regarding all eight measures, which is a prerequisite for studying their associations over time.

Girls reported higher averages in SMU problems, SMU intensity, depressive symptoms, upward social comparisons, and face-to-face contact, and lower averages in life satisfaction and cybervictimization than boys. Adolescents who attended pre-vocational education reported higher levels of SMU problems, SMU intensity, cybervictimization, and face-to-face contact, and lower levels of upward social comparison and subjective school achievements than adolescents who attended pre-university education. Adolescents who attended intermediate education showed higher reports of SMU problems, cybervictimization, and face-to-face contact, and lower reports of subjective school achievements than adolescents who attended pre-university education. Finally, immigrant adolescents reported lower levels of subjective school achievements and less face-to-face contact than non-immigrant adolescents. The revealed associations between adolescents' demographics and the study measures do not influence the bidirectional associations from our main analyses, as the RI-CLPM controls for all possible stable confounders (Hamaker et al., 2015).



## Direct Cross-Lagged Associations Between SMU and Mental Health

Table 6.3 reports the within-person auto-regressive and cross-lagged associations between SMU intensity, SMU problems, depressive symptoms (M1a), and life satisfaction (M2a). Both models had excellent model fit (M1a: CFI = 0.997, TLI = 0.980, RMSEA = 0.043, SRMR = 0.010; M2a: CFI = 0.996, TLI = 0.975, RMSEA = 0.047, SRMR = 0.011).

### *SMU Intensity and Mental Health*

The cross-lagged associations between SMU intensity and both mental health indicators were all non-significant. This means that adolescents whose SMU intensity increased did not report increased depressive symptoms or decreased life satisfaction one year later. Reversely, adolescents whose depressive symptoms increased, or whose life satisfaction decreased, did not report increased SMU intensity one year later. Thus, conform our expectations, SMU intensity and mental health were not associated in any direction.

**Table 6.3**

*RI-CLPMs on Depressive symptoms and Life Satisfaction, Within-Person Cross-Lagged Associations (n = 2,109)*

| **M1a** | **SMU problems T2** | | **SMU intensity T2** | | **Depressive symptoms T2** | |
|---|---|---|---|---|---|---|
| | ***β*** | **(*SE*)** | ***β*** | **(*SE*)** | ***β*** | **(*SE*)** |
| **SMU problems T1** | 0.695*** | (0.039) | 0.185** | (0.058) | 0.176** | (0.064) |
| **SMU intensity T1** | 0.094** | (0.033) | 0.335* | (0.130) | 0.027 | (0.058) |
| **Depressive symptoms T1** | 0.062 | (0.032) | 0.013 | (0.053) | 0.257 | (0.131) |
| | **SMU problems T3** | | **SMU intensity T3** | | **Depressive symptoms T3** | |
| | ***β*** | **(*SE*)** | ***β*** | **(*SE*)** | ***β*** | **(*SE*)** |
| **SMU problems T2** | 0.746*** | (0.032) | 0.247** | (0.089) | 0.086* | (0.043) |
| **SMU intensity T2** | 0.027 | (0.038) | 0.374* | (0.178) | -0.001 | (0.046) |
| **Depressive symptoms T2** | 0.020 | (0.026) | 0.001 | (0.063) | 0.421*** | (0.078) |
| **M2a** | **SMU problems T2** | | **SMU intensity T2** | | **Life satisfaction T2** | |
| | ***β*** | **(*SE*)** | ***β*** | **(*SE*)** | ***β*** | **(*SE*)** |
| **SMU problems T1** | 0.703*** | (0.038) | 0.185** | (0.057) | -0.163*** | (0.043) |
| **SMU intensity T1** | 0.096** | (0.035) | 0.334** | (0.128) | -0.010 | (0.061) |
| **Life satisfaction T1** | -0.050 | (0.029) | -0.024 | (0.050) | 0.084 | (0.097) |
| | **SMU problems T3** | | **SMU intensity T3** | | **Life satisfaction T3** | |
| | ***β*** | **(*SE*)** | ***β*** | **(*SE*)** | ***β*** | **(*SE*)** |
| **SMU problems T2** | 0.750*** | (0.030) | 0.249* | (0.098) | -0.116* | (0.048) |
| **SMU intensity T2** | 0.028 | (0.038) | 0.374* | (0.177) | -0.022 | (0.064) |
| **Life satisfactionT2** | -0.008 | (0.024) | 0.009 | (0.063) | 0.113 | (0.066) |

*Notes.* RI-CLPM = random intercept cross-lagged panel model. SMU = social media use; β = STDYX-standardized; SE = standard error. Results in table show the average estimates over 20 imputed datasets of plausible values. All models included correlations between (the residuals of the) measurements in the same year (results not shown). *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

### *SMU Problems and Mental Health*

In contrast, adolescents whose SMU problems increased reported increased depressive symptoms one year later (M1a: $\beta_{T1,T2} = 0.176$, $p = 0.006$ and $\beta_{T2,T3} = 0.086$, $p = 0.046$). Adolescents whose SMU problems increased showed decreased life satisfaction one year later (M2a: $\beta_{T1,T2} = -0.163$, $p < 0.001$ and $\beta_{T2,T3} = -0.116$, $p = 0.017$). The reverse paths were non-significant, which means that adolescents whose depressive symptoms increased or whose life satisfaction decreased did not show increased SMU problems one year later. Thus, consistent across waves, we observed a unidirectional association between SMU problems and low mental health, which partially confirms our expectations.

## Indirect Cross-Lagged Associations Between SMU and Mental Health

The RI-CLPM with depressive symptoms (M1a) was extended with four mediators, namely upward social comparisons, cybervictimization, subjective school achievements, and face-to-face contact, with one mediator per model (M1b-e). Similarly, we extended the RI-CLPM with life satisfaction (M2a) with the four mediators (M2b-e). Figure 6.3 displays the models where we found significant cross-lagged paths with the mediators. All estimates of these models can be found in the Appendix (Tables A6.1 and A6.2).

### *SMU Intensity and Mental Health*

Adolescents' changes in SMU intensity, depressive symptoms, and life satisfaction did not precede or follow from changes in upward social comparisons, cybervictimization, subjective school achievements, or face-to-face contact with friends (Appendix, Tables A6.1 and A6.2). Hence, in line with our expectations, SMU intensity and mental health were neither directly, nor indirectly associated over time in any direction.



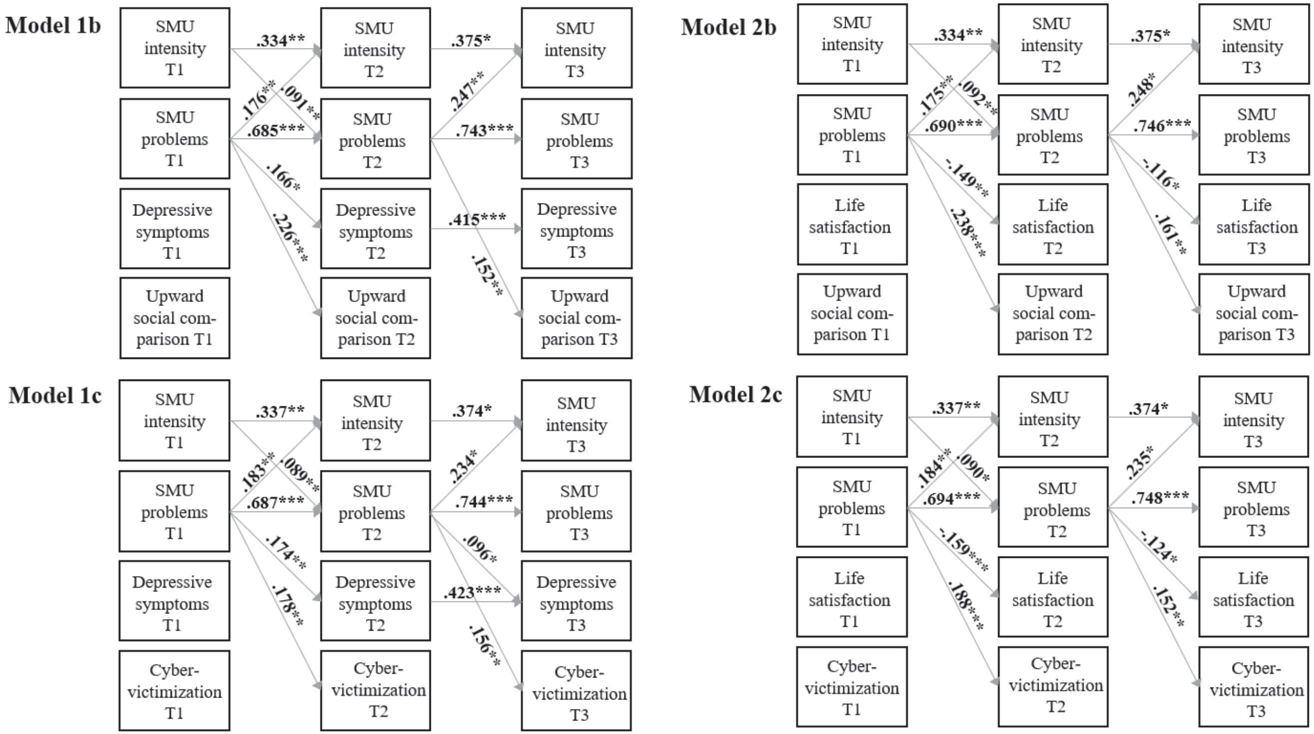
### *SMU Problems and Mental Health*

Figure 6.3 shows that adolescents whose SMU problems increased reported increased upward social comparisons (M1b: $\beta_{T1,T2}$ = 0.226, $p$ < 0.001 and $\beta_{T2,T3}$ = 0.152, $p$ = 0.001) and cybervictimization (M1c: $\beta_{T1,T2}$ = 0.178, $p$ = 0.001 and $\beta_{T2,T3}$ = 0.156, $p$ = 0.003) in the next year. However, in turn, adolescents' increased upward social comparisons and cybervictimization did not predict increased depressive symptoms or decreased life satisfaction one year later. Increases in SMU problems were not associated with decreases in school achievements and face-to-face contact one year later, and decreases in school achievements and face-to-face contact in turn were not associated with increases in depressive symptoms or decreases in life satisfaction one year later (Appendix Tables A6.1 and A6.2). Therefore, we did not find evidence that SMU problems decreased mental health indirectly through any of the four suggested mediators.

Reversely, changes in depressive symptoms and life satisfaction did not predict changes in upward social comparisons, cybervictimization, subjective

**Figure 6.3**

*Significant Associations From the RI-CLPMs*




*Notes.* The figure displays the significant auto-regressive and (cross-)lagged standardized associations between the within-person values of the measures (see Appendix Tables A6.1 and A6.2 for all estimates).
* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

school achievements, or face-to-face contact with friends one year later, and in turn, changes in these four suggested mediators did not predict changes in SMU problems one year later (Figure 6.3, Appendix Tables A6.1 and A6.2). Thus, in contrast to our expectations, we did not observe any direct or indirect effects of low mental health on SMU problems.

## Additional Findings

### *Additional Mediations*

The analyses provided several additional insights. Table 6.3 shows that adolescents whose SMU intensity increased in T1 reported increased SMU problems in T2 (M1a: $\beta = 0.094$, $p = 0.002$), and that in turn, adolescents whose SMU problems increased in T2 showed increased depressive symptoms in T3 (M1a: $\beta = 0.086$, $p = 0.046$) and decreased life satisfaction in T3 (M2a: $\beta = -0.116$, $p = 0.017$). However, mediation analysis showed that the indirect path between SMU intensity in T1 via SMU problems in T2 to depressive symptoms in T3 was not significant ($\beta = 0.008$, $p = 0.093$). Also, the indirect path between SMU intensity in T1 via SMU problems in T2 to life satisfaction in T3 was not significant ($\beta = -0.011$, $p = 0.060$). In addition, increases in SMU intensity in T1 were indirectly associated with increases in upward social comparisons and cybervictimization in T3 via SMU problems in T2 (Figure 6.3). Mediation analyses, however, showed that the strength of these indirect associations was close to zero ($\beta = 0.015$, $p = 0.027$ and $\beta = 0.014$, $p = 0.049$, respectively).

### *Correlations Within the Same Year*

The RI-CLPMs also included correlations between (the residuals of the) within-person values of our measures within the same year. The Appendix reports these correlations from M1b to M1e and M2b to M2e (Tables A6.3 and A6.4). Results showed that, although we did not observe any cross-lagged associations between SMU intensity and mental health, adolescents whose SMU intensity increased in T1 reported increased depressive symptoms within the same year (M1b: $r = 0.155$, $p = 0.015$). Increases in SMU intensity did not co-occur with decreases in life satisfaction within the same year in any of the waves. Also, adolescents who reported increased SMU intensity in T1 reported increased upward social comparisons (M1b: $r = 0.170$, $p < 0.001$), increased cybervictimization (M1c: $r$ = 0.187, $p$ < 0.001), and decreased subjective school achievements (M1d: $r$ = -0.116, $p$ = 0.009) in the same year. In addition, adolescents with increased SMU intensity in T1 or T2 reported increased face-to-face contact within the same year (M1e: $r_{T1}$ = 0.195, $p$ < 0.001 and $r_{T2}$ = 0.117, $p$ = 0.022). However, we cannot infer directionality from these correlations. Moreover, correlations with SMU intensity in T1 may be driven by SMU problems in T1, as correlations in T1 did not take into account variance due to T1-covariates (Figure 6.2).

Also, we did not find evidence that SMU problems decreased mental health via upward social comparisons and cybervictimization, because increased upward social comparisons and cybervictimization in T2 did not predict decreased mental health one year later. However, adolescents' increases in upward social comparisons in T2 were associated with increases in depressive symptoms (M1b: $r$ = 0.204, $p$ = 0.001) and decreases in life satisfaction (M2b: $r$ = -0.172, $p$ = 0.006) within the same year. Also, increases in cybervictimization in T2 co-occurred with increases in depressive symptoms within the same year (M1c: $r$ = 0.114, $p$ = 0.030). Yet, we cannot infer directionality from these correlations.

### *Gender Differences*

Finally, we examined whether our results were robust to gender. Researchers proposed that girls have a higher tendency to ruminate about content on social media and to compare themselves with others online than boys (Nesi & Prinstein, 2015; Underwood & Ehrenreich, 2017). Consequently, girls may be more prone to adverse effects of SMU (problems) than boys. Gender differences were investigated using multiple group RI-CLPMs (Mulder & Hamaker, 2021). More specifically, we estimated RI-CLPMs where all parameters were free to vary across boys and girls. In these models, we obtained $z$-scores for the differences in the strength of the cross-lagged parameters between the two groups. Findings of these results may be consulted in the Appendix (Tables A6.5 and A6.6). The analyses showed that although the strength and significance of the cross-lagged parameters differed slightly between boys and girls, these differences were not significant in any of the waves. These findings suggest that the associations are equally strong for boys and girls.

## Discussion

The present study investigated bidirectional associations between SMU and mental health using longitudinal data collected among adolescents. In doing so, we distinguished between SMU intensity and addiction-like SMU problems. We also examined whether the proposed bidirectional associations were mediated by upward social comparisons, cybervictimization, decreased subjective school achievements, and less face-to-face contact. Findings showed that adolescents whose SMU problems increased reported increased depressive symptoms and decreased life satisfaction one year later. Also, SMU problems predicted increases in upward social comparisons and cybervictimization over time. Yet this, in turn, did not predict increases in depressive symptoms or decreases in life satisfaction over time, suggesting that upward social comparisons and cybervictimization did not mediate the observed effect of SMU problems on mental health. Reversely, increased depressive symptoms or decreased life satisfaction did not predict increased SMU problems one year later, neither directly nor indirectly through any of the mediators. We did not observe any direct or indirect associations between SMU intensity and mental health over time: Adolescents whose SMU intensity increased did not report increased depressive symptoms or decreased life satisfaction one year later, and neither vice versa.

Scholars have raised concerns about the adverse effects of SMU among adolescents (Primack & Escobar-Viera, 2017; Underwood & Ehrenreich, 2017). The present study suggests that particularly adolescents who show addiction-like SMU problems, but not adolescents who solely show high SMU intensity, are at risk for decreases in mental health. More specifically, being unable to control SMU impulses, constantly thinking about SMU, feeling bad when SMU is restricted, or attaching vital importance to SMU seem to evoke detrimental consequences to adolescents' mental health, rather than using social media a lot. Thus, adverse effects of SMU may depend on the extent to which adolescents have agency over their SMU, and not on their frequency of SMU. To that end, adolescents who engage in high SMU intensity without any SMU problems may be well able to regulate their SMU; their SMU may not necessarily interfere with life domains relevant to their mental health. After all, nowadays, high SMU intensity has become an integral part of adolescents' daily lives, and most adolescents use social media intensively to maintain social contact with peers (Boyd, 2014). Moreover, the finding that SMU problems and SMU intensity have differential associations with mental health supports the suggestion that these two types of SMU should be regarded as two separate dimensions of SMU.

Our suggestion that adolescents' high SMU intensity does not impair mental health challenges previous research that showed a negative association between SMU intensity and mental health (Kelly et al., 2018; Riehm et al., 2019; Twenge, Joiner, et al., 2018; Twenge & Campbell, 2018). This discrepancy could be related to the fact that most previous studies on the association between SMU intensity and mental health did not control for SMU problems. The few studies that did so showed that when SMU intensity and SMU problems are studied in one model, only or particularly SMU problems are associated with poor mental health (Boer, Van den Eijnden, et al., 2020; Shensa et al., 2017; Van den Eijnden et al., 2018). Hence, previously found negative associations between SMU intensity and mental health were potentially confounded by unobserved SMU problems. Moreover, the discrepancy may be related to the fact that previous longitudinal studies that showed that high SMU intensity decreased mental health over time were based on analytical approaches that lack separation of within- and between-person variance (Frison & Eggermont, 2017; Riehm et al., 2019; Vannucci & McCauley Ohannessian, 2019). As a result, previously found effects over time were possibly confounded by unobserved time-invariant traits (Hamaker et al., 2015; Orben, 2020a), such as personality. The analysis of the present study controlled for this possibility, which makes results that are inconsistent with previous longitudinal studies plausible (Hamaker et al., 2015). Longitudinal studies that adopted a comparable analytical approach as in the present study showed, in line with our findings, that adolescents' SMU intensity was not or only weakly associated with poorer mental health (Coyne et al., 2020; George et al., 2020; Houghton et al., 2018; Jensen et al., 2019; Orben et al., 2019). Thus, there is increasing evidence that engaging in high SMU intensity by itself does not impose a risk to adolescents' mental health.

Yet, adolescents who show increased SMU intensity may be vulnerable to other risks, as our findings showed that increased SMU intensity predicted increased SMU problems one year later, although this was only observed from T1 to T2. More research on this potential association, focusing on for which group of adolescents high SMU intensity turns into developing SMU problems, is considered as an important direction for future research. At the same time, high SMU intensity may also be beneficial, as our findings showed that adolescents whose SMU intensity increased reported increased face-to-face peer contact within the same year (in T1 and T2). Although we cannot derive directionality from this correlation, the finding refutes the idea that time spent on social media replaces time spent with friends offline, as frequently proposed (Twenge, Joiner, et al., 2018; Twenge & Campbell, 2018; Underwood & Ehrenreich, 2017; Wallsten, 2013). In line with our finding, other researchers also reported a positive association between SMU intensity and offline social interaction with friends or perceived friends support (Boer, Van den Eijnden, et al., 2020; De Looze et al., 2019; Valkenburg & Peter, 2007). High SMU intensity may be used to maintain contact with existing friends and may thereby be indicative of social involvement with peers, rather than neglecting friendships. Furthermore, research has shown that the more adolescents socialize with peers on social network sites, the less lonely they feel, which supports the idea that SMU may be used to strengthen and maintain friendships (Apaolaza et al., 2013).



In contrast, findings of the present study underline the potential harmful effect of SMU problems to adolescents' mental health. Moreover, SMU problems predicted increased levels of upward social comparisons and cybervictimization over time. These increases, in turn, did not decrease mental health one year later, which implies that upward social comparison and cybervictimization did not mediate the negative effect of SMU problems on mental health. However, adolescents' increases in upward social comparisons and cybervictimization co-occurred with decreases in mental health within the same year. Therefore, and because of previously found effects of social comparisons and cybervictimization on mental health (Feinstein et al., 2013; Roeder et al., 2016), there may have been a mediating effect, but the measurements were possibly too far apart to observe it. For example, research shows that while adolescents experience increased emotional arousal shortly after posting on Facebook, this effect does not persist in the long run (Bayer et al., 2018). Correspondingly, when adolescents experience cybervictimization on social media or increased levels of upward social comparisons due to viewing social media content, they may experience more depressive symptoms or less life satisfaction within the same time frame, but this decrement in mental health may not persist for a year. In other words, mediating processes whereby adolescents' SMU problems decrease mental health through upward social comparisons and cybervictimization may emerge within a shorter time frame. More longitudinal research, using shorter time intervals, is required to verify this suggestion.

In addition, our results suggest that the negative association between SMU problems and mental health was unidirectional, thus that decreases in mental health did not lead to increases in SMU problems. In our additional analysis on gender differences, the unidirectional finding remained stable, suggesting that this accounted both for boys and girls. Hence, we did not find support for the cognitive behavioral model of addiction, which posits that pre-existing psychopathology drive the development of addiction-like internet-related behaviors (Davis, 2001; Griffiths, 2013). However, other longitudinal research among adults showed that, in line with the cognitive behavioral model, decreased life satisfaction predicted increased social media self-control failure (Du et al., 2021), which is also an element of SMU problems. An explanation for the seemingly contrasting findings might be that adults with poor mental health may be more sensitive to developing SMU problems than adolescents with mental health impairments. It has been proposed that while adults with mental health problems may engage in addiction-like SMU to alleviate their problems, adolescents with poor mental health may refrain from social media because SMU further deteriorates their mental health, as they may be more sensitive to comparing themselves with others on social media than adults (Ho et al., 2017). Alternatively, the conclusion that mental health problems do not underlie adolescents' SMU problems may be premature. Although the cognitive behavioral model postulates that pre-existing psychopathology is a necessary condition for the development of addiction symptoms, pre-existing psychopathology does not by definition lead to developing addiction-like behavior (Davis, 2001). To that end, mental health problems may pose a risk for developing SMU problems for a specific group of adolescents, which is possibly not detected in our analysis on a heterogeneous sample. Therefore, more longitudinal research on the effect of poor mental health on SMU problems is warranted, focusing on potential moderators of the effect (e.g., social anxiety, personality traits).

## Strengths and Limitations

The present study has important strengths, such as the conceptual difference between SMU intensity and SMU problems in relation with mental health, the definition of mental health that encompasses the presence of wellbeing as well as absence of mental illnesses, the longitudinal data and innovative modelling techniques that provide insight into the directionality of associations, and the number of mediators investigated that allow for a more in-depth understanding of associations. However, findings of this study should be interpreted in light of several limitations.

First, our conceptualization of SMU intensity combines passive (e.g., viewing social media) and active social media activities (e.g., responding to messages). Disentangling the independent effects of passive and active SMU intensity was beyond the scope of the present study. Our findings should be interpreted in light of this operationalization: When examining overall SMU intensity, SMU intensity and mental health do not seem to be associated over time. However, it has been proposed that particularly passive SMU threatens mental health (Odgers & Jensen, 2020; Orben, 2020a), although experimental and longitudinal research suggests that this depends on the characteristics of the adolescent (Beyens, Pouwels, Valkenburg, et al., 2020; De Vries et al., 2018; Wenninger et al., 2014). To consolidate our conclusion that SMU intensity does not impair mental health, more research testing the effects of passive and active SMU intensity separately is essential. To that end, the use of objective measures, such as tracked time spent or frequency of active and passive SMU, would be promising, as such measures provide more reliable estimates of SMU than self-report measures (Junco, 2013).

Second, we proposed that mental health problems could both cause and result from SMU problems. However, it could be argued that this proposition reflects a circular relationship between mental health and SMU problems rather than a bidirectional association. Mental health problems that cause SMU problems may differ from mental health problems that arise from SMU problems. More specifically, while it is argued that pre-existing pathological mental health problems underly the development of SMU problems (Davis, 2001; Griffiths, 2013), SMU problems may not lead to pathological levels of mental health problems, but rather to decreases in mental health in general. Third, although the yearly time intervals of the repeated measures provide insight into potential long-term effects over time, such time intervals also have drawbacks. More specifically, behaviors may influence each other within a shorter time frame (Orben, 2020a), which could not be captured with the research design of the present study. Therefore, more longitudinal research replicating our study using more intensive longitudinal data, such as daily measures of SMU and mental health, is considered as an important direction for future research. Fourth, as is typical for longitudinal studies, the present study dealt with considerable dropout of participants. Although the dropout in the present study was not selective and the associations between our study variables and dropout were small, dropout remained a limitation. We aimed to limit the bias that is typically associated with dropout by retaining all adolescents in the analyses.

## Conclusion

Most adolescents spend considerable time on social media, which raises concerns among many. Findings of the present study emphasize the importance of considering SMU intensity and SMU problems as two distinct behaviors, because our results suggest that particularly SMU problems pose a risk to adolescents' mental health. The reverse pattern was not observed, which suggests that poor mental health does not lead to developing SMU problems. Moreover, SMU problems were found to increase upward social comparisons and cybervictimization, which implies that adolescents with SMU problems face multiple adversities. High SMU intensity and mental health were not associated in any direction. The findings imply that policies and guidelines aimed at identifying, preventing, or informing about unhealthy SMU should focus on SMU problems rather than on high SMU intensity. More longitudinal research replicating our findings is warranted and may advance our insight into the origins of SMU problems as well as the underlying mechanisms explaining the link between SMU problems and low mental health.

# Appendix

**Table A6.1**

*RI-CLPMs on Depressive Symptoms Extended With Mediators, Within-Person (Cross-)Lagged Associations (n = 2,109)*

| **M1b** | **SMU problems T2** | | **SMU intensity T2** | | **Depressive symptoms T2** | | **Upward social comparisons T2** | |
|---|---|---|---|---|---|---|---|---|
| | ***β*** | **(*SE*)** | ***β*** | **(*SE*)** | ***β*** | **(*SE*)** | ***β*** | **(*SE*)** |
| **SMU problems T1** | 0.685*** | (0.041) | 0.176** | (0.057) | 0.166* | (0.064) | 0.226*** | (0.060) |
| **SMU intensity T1** | 0.091** | (0.034) | 0.334** | (0.129) | 0.027 | (0.058) | 0.042 | (0.075) |
| **Depressive symptoms T1** | 0.056 | (0.032) | 0.009 | (0.053) | 0.253 | (0.129) | 0.073 | (0.079) |
| **Upward social comparisons T1** | 0.044 | (0.026) | 0.034 | (0.045) | 0.027 | (0.066) | 0.006 | (0.103) |
| | **SMU problems T3** | | **SMU intensity T3** | | **Depressive symptoms T3** | | **Upward social comparisons T3** | |
| | ***β*** | **(*SE*)** | ***β*** | **(*SE*)** | ***β*** | **(*SE*)** | ***β*** | **(*SE*)** |
| **SMU problems T2** | 0.743*** | (0.032) | 0.247** | (0.092) | 0.079 | (0.043) | 0.152** | (0.044) |
| **SMU intensity T2** | 0.026 | (0.038) | 0.375* | (0.178) | -0.002 | (0.046) | 0.009 | (0.058) |
| **Depressive symptoms T2** | 0.017 | (0.027) | 0.001 | (0.065) | 0.415*** | (0.078) | 0.052 | (0.066) |
| **Upward social comparisons T2** | 0.015 | (0.025) | 0.000 | (0.069) | 0.029 | (0.046) | 0.104 | (0.096) |
| **M1c** | **SMU Problems T2** | | **SMU intensity T2** | | **Depressive symptoms T2** | | **Cybervictimization T2** | |
| | ***β*** | **(*SE*)** | ***β*** | **(*SE*)** | ***β*** | **(*SE*)** | ***β*** | **(*SE*)** |
| **SMU problems T1** | 0.687*** | (0.039) | 0.183** | (0.059) | 0.174** | (0.064) | 0.178** | (0.053) |
| **SMU intensity T1** | 0.089** | (0.034) | 0.337** | (0.129) | 0.026 | (0.059) | 0.107 | (0.063) |
| **Depressive symptoms T1** | 0.059 | (0.033) | 0.013 | (0.054) | 0.257 | (0.131) | 0.016 | (0.070) |
| **Cybervictimization T1** | 0.036 | (0.027) | 0.006 | (0.045) | -0.004 | (0.055) | 0.156 | (0.099) |
| | **SMU problems T3** | | **SMU intensity T3** | | **Depressive symptoms T3** | | **Cybervictimization T3** | |
| | ***β*** | **(*SE*)** | ***β*** | **(*SE*)** | ***β*** | **(*SE*)** | ***β*** | **(*SE*)** |
| **SMU problems T2** | 0.744*** | (0.032) | 0.234* | (0.090) | 0.096* | (0.046) | 0.156** | (0.053) |
| **SMU intensity T2** | 0.026 | (0.038) | 0.374* | (0.177) | 0.001 | (0.046) | 0.030 | (0.058) |
| **Depressive symptoms T2** | 0.019 | (0.026) | -0.004 | (0.063) | 0.423*** | (0.077) | -0.030 | (0.060) |
| **Cybervictimization T2** | 0.009 | (0.024) | 0.045 | (0.064) | -0.036 | (0.042) | 0.100 | (0.091) |
| **M1d** | **SMU problems T2** | | **SMU intensity T2** | | **Depressive symptoms T2** | | **Subjective school achievements T2** | |
| | ***β*** | **(*SE*)** | ***β*** | **(*SE*)** | ***β*** | **(*SE*)** | ***β*** | **(*SE*)** |
| **SMU problems T1** | 0.695*** | (0.039) | 0.182** | (0.057) | 0.176** | (0.065) | -0.039 | (0.036) |
| **SMU intensity T1** | 0.093** | (0.033) | 0.336* | (0.132) | 0.026 | (0.060) | -0.078 | (0.052) |
| **Depressive symptoms T1** | 0.062 | (0.032) | 0.011 | (0.053) | 0.257 | (0.132) | -0.006 | (0.056) |
| **Subj. school achievements T1** | -0.001 | (0.023) | -0.037 | (0.043) | 0.000 | (0.058) | 0.289*** | (0.063) |
| | **SMU problems T3** | | **SMU intensity T3** | | **Depressive symptoms T3** | | **Subjective school achievements T3** | |
| | ***β*** | **(*SE*)** | ***β*** | **(*SE*)** | ***β*** | **(*SE*)** | ***β*** | **(*SE*)** |
| **SMU problems T2** | 0.746*** | (0.032) | 0.240** | (0.088) | 0.088* | (0.043) | -0.062 | (0.041) |
| **SMU intensity T2** | 0.027 | (0.037) | 0.376* | (0.177) | 0.000 | (0.047) | -0.032 | (0.055) |
| **Depressive symptoms T2** | 0.021 | (0.026) | -0.004 | (0.063) | 0.422*** | (0.079) | -0.017 | (0.055) |
| **Subj. school achievements T2** | 0.004 | (0.023) | -0.053 | (0.053) | 0.020 | (0.035) | 0.078 | (0.090) |
| **M1e** | **SMU Problems T2** | | **SMU intensity T2** | | **Depressive symptoms T2** | | **Face-to-face contact T2** | |
| | ***β*** | **(*SE*)** | ***β*** | **(*SE*)** | ***β*** | **(*SE*)** | ***β*** | **(*SE*)** |
| **SMU problems T1** | 0.695*** | (0.039) | 0.184** | (0.057) | 0.177** | (0.064) | 0.032 | (0.041) |
| **SMU intensity T1** | 0.095** | (0.034) | 0.326* | (0.127) | 0.030 | (0.058) | 0.084 | (0.059) |
| **Depressive symptoms T1** | 0.061 | (0.032) | 0.012 | (0.054) | 0.256* | (0.130) | -0.012 | (0.067) |
| **Face-to-face contact T1** | -0.003 | (0.024) | 0.055 | (0.047) | -0.018 | (0.053) | 0.286** | (0.103) |
| | **SMU problems T3** | | **SMU intensity T3** | | **Depressive symptoms T3** | | **Face-to-face contact T3** | |
| | ***β*** | **(*SE*)** | ***β*** | **(*SE*)** | ***β*** | **(*SE*)** | ***β*** | **(*SE*)** |
| **SMU problems T2** | 0.746*** | (0.031) | 0.245** | (0.089) | 0.086* | (0.044) | 0.051 | (0.041) |
| **SMU intensity T2** | 0.028 | (0.037) | 0.371* | (0.178) | -0.001 | (0.045) | 0.009 | (0.065) |
| **Depressive symptoms T2** | 0.020 | (0.026) | 0.002 | (0.063) | 0.420*** | (0.078) | -0.024 | (0.051) |
| **Face-to-face contact T2** | -0.003 | (0.027) | 0.032 | (0.064) | 0.000 | (0.038) | 0.400*** | (0.085) |

*Notes.* RI-CLPM = random intercept cross-lagged panel model. SMU = social media use; β = STDYX-standardized; SE = standard error. Results in table show the average estimates over 20 imputed datasets of plausible values. All models included (residual) correlations between measurements in the same year (estimates presented in Table A6.3).
*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

**Table A6.2**

*RI-CLPMs on Life Satisfaction Extended With Mediators, Within-Person (Cross-)Lagged Associations (n = 2,109)*

| M2b | SMU problems T2 | | SMU intensity T2 | | Life satisfaction T2 | | Upward social comparisons T2 | |
|---|---|---|---|---|---|---|---|---|
| | ***β*** | ***(SE)*** | ***β*** | ***(SE)*** | ***β*** | ***(SE)*** | ***β*** | ***(SE)*** |
| **SMU problems T1** | 0.690*** | (0.041) | 0.175** | (0.057) | -0.149** | (0.047) | 0.238*** | (0.059) |
| **SMU intensity T1** | 0.092** | (0.035) | 0.334** | (0.127) | 0.008 | (0.061) | 0.043 | (0.076) |
| **Life satisfaction T1** | -0.046 | (0.028) | -0.021 | (0.050) | 0.079 | (0.096) | -0.042 | (0.070) |
| **Upward social comparisons T1** | 0.051 | (0.026) | 0.032 | (0.046) | -0.044 | (0.053) | 0.014 | (0.101) |
| | **SMU problems T3** | | **SMU intensity T3** | | **Life satisfaction T3** | | **Upward social comparisons T3** | |
| | ***β*** | ***(SE)*** | ***β*** | ***(SE)*** | ***β*** | ***(SE)*** | ***β*** | ***(SE)*** |
| **SMU problems T2** | 0.746*** | (0.031) | 0.248* | (0.100) | -0.116* | (0.053) | 0.161** | (0.044) |
| **SMU intensity T2** | 0.027 | (0.038) | 0.375* | (0.177) | -0.022 | (0.065) | 0.011 | (0.059) |
| **Life satisfaction T2** | -0.005 | (0.024) | 0.009 | (0.063) | 0.112 | (0.066) | -0.020 | (0.044) |
| **Upward social comparisons T2** | 0.017 | (0.025) | 0.001 | (0.067) | 0.002 | (0.055) | 0.109 | (0.094) |
| **M2c** | **SMU Problems T2** | | **SMU intensity T2** | | **Life satisfaction T2** | | **Cybervictimization T2** | |
| | ***β*** | ***(SE)*** | ***β*** | ***(SE)*** | ***β*** | ***(SE)*** | ***β*** | ***(SE)*** |
| **SMU problems T1** | 0.694*** | (0.039) | 0.184** | (0.058) | -0.159*** | (0.045) | 0.188*** | (0.048) |
| **SMU intensity T1** | 0.090* | (0.035) | 0.337** | (0.127) | -0.008 | (0.061) | 0.106 | (0.063) |
| **Life satisfaction T1** | -0.047 | (0.028) | -0.022 | (0.050) | 0.086 | (0.098) | 0.037 | (0.061) |
| **Cybervictimization T1** | 0.040 | (0.027) | 0.005 | (0.046) | -0.007 | (0.054) | 0.164 | (0.100) |
| | **SMU problems T3** | | **SMU intensity T3** | | **Life satisfaction T3** | | **Cybervictimization T3** | |
| | ***β*** | ***(SE)*** | ***β*** | ***(SE)*** | ***β*** | ***(SE)*** | ***β*** | ***(SE)*** |
| **SMU problems T2** | 0.748*** | (0.031) | 0.235* | (0.097) | -0.124* | (0.048) | 0.152** | (0.050) |
| **SMU intensity T2** | 0.027 | (0.038) | 0.374* | (0.176) | -0.023 | (0.065) | 0.029 | (0.058) |
| **Life satisfaction T2** | -0.007 | (0.023) | 0.014 | (0.063) | 0.117 | (0.067) | 0.018 | (0.048) |
| **Cybervictimization T2** | 0.010 | (0.024) | 0.045 | (0.064) | 0.031 | (0.050) | 0.099 | (0.091) |
| **M2d** | **SMU problems T2** | | **SMU intensity T2** | | **Life satisfaction T2** | | **Subjective school achievements T2** | |
| | ***β*** | ***(SE)*** | ***β*** | ***(SE)*** | ***β*** | ***(SE)*** | ***β*** | ***(SE)*** |
| **SMU problems T1** | 0.704*** | (0.038) | 0.182** | (0.056) | -0.160*** | (0.044) | -0.042 | (0.033) |
| **SMU intensity T1** | 0.094** | (0.035) | 0.336** | (0.130) | -0.007 | (0.062) | -0.078 | (0.052) |
| **Life satisfaction T1** | -0.050 | (0.029) | -0.021 | (0.050) | 0.080 | (0.096) | -0.006 | (0.046) |
| **Subj. school achievements T1** | 0.001 | (0.023) | -0.035 | (0.043) | 0.048 | (0.052) | 0.290*** | (0.064) |
| | **SMU problems T3** | | **SMU intensity T3** | | **Life satisfaction T3** | | **Subjective school achievements T3** | |
| | ***β*** | ***(SE)*** | ***β*** | ***(SE)*** | ***β*** | ***(SE)*** | ***β*** | ***(SE)*** |
| **SMU problems T2** | 0.750*** | (0.030) | 0.242* | (0.096) | -0.115* | (0.048) | -0.067 | (0.039) |
| **SMU intensity T2** | 0.028 | (0.037) | 0.376* | (0.175) | -0.023 | (0.064) | -0.034 | (0.055) |
| **Life satisfaction T2** | -0.009 | (0.024) | 0.014 | (0.063) | 0.112 | (0.066) | -0.004 | (0.052) |
| **Subj. school achievements T2** | 0.004 | (0.024) | -0.054 | (0.053) | 0.011 | (0.047) | 0.081 | (0.091) |
| **M2e** | **SMU Problems T2** | | **SMU intensity T2** | | **Life satisfaction T2** | | **Face-to-face contact T2** | |
| | ***β*** | ***(SE)*** | ***β*** | ***(SE)*** | ***β*** | ***(SE)*** | ***β*** | ***(SE)*** |
| **SMU problems T1** | 0.703*** | (0.038) | 0.182** | (0.057) | -0.166*** | (0.043) | 0.038 | (0.037) |
| **SMU intensity T1** | 0.096** | (0.036) | 0.325** | (0.125) | -0.022 | (0.061) | 0.086 | (0.058) |
| **Life satisfaction T1** | -0.051 | (0.029) | -0.028 | (0.050) | 0.079 | (0.096) | 0.038 | (0.049) |
| **Face-to-face contact T1** | 0.001 | (0.024) | 0.058 | (0.046) | 0.068 | (0.054) | 0.281** | (0.102) |
| | **SMU problems T3** | | **SMU intensity T3** | | **Life satisfaction T3** | | **Face-to-face contact T3** | |
| | ***β*** | ***(SE)*** | ***β*** | ***(SE)*** | ***β*** | ***(SE)*** | ***β*** | ***(SE)*** |
| **SMU problems T2** | 0.750*** | (0.030) | 0.246* | (0.097) | -0.117* | (0.048) | 0.044 | (0.042) |
| **SMU intensity T2** | 0.028 | (0.037) | 0.371* | (0.176) | -0.024 | (0.064) | 0.009 | (0.065) |
| **Life satisfaction T2** | -0.008 | (0.024) | 0.004 | (0.064) | 0.111 | (0.067) | 0.004 | (0.046) |
| **Face-to-face contact T2** | -0.003 | (0.027) | 0.031 | (0.065) | 0.021 | (0.048) | 0.399*** | (0.089) |

*Notes.* RI-CLPM = random intercept cross-lagged panel model. SMU = social media use; β = STDYX-standardized; SE = standard error. Results in table show the average estimates over 20 imputed datasets of plausible values. All models included (residual) correlations between measurements in the same year (estimates presented in Table A6.4).
*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

6

**Table A6.3**

*RI-CLPMs on Depressive symptoms, Within-Person (Residual) Correlations Within Same Year (n = 2,109)*

| **M1b** | **SMU problems** | | | **SMU intensity** | | | **Depressive symptoms** | | |
|---|---|---|---|---|---|---|---|---|---|
| | ***r* (T1)** | ***r* (T2)** | ***r* (T3)** | ***r* (T1)** | ***r* (T2)** | ***r* (T3)** | ***r* (T1)** | ***r* (T2)** | ***r* (T3)** |
| **SMU intensity** | 0.304*** | 0.159** | 0.057 | | | | | | |
| **Depressive symptoms** | 0.325*** | 0.138*** | 0.053 | 0.155* | 0.056 | 0.000 | | | |
| **Upward social comparisons** | 0.306*** | 0.157*** | 0.056 | 0.170*** | 0.074 | -0.012 | 0.260*** | 0.204** | 0.068 |
| **M1c** | **SMU problems** | | | **SMU intensity** | | | **Depressive symptoms** | | |
| | ***r* (T1)** | ***r* (T2)** | ***r* (T3)** | ***r* (T1)** | ***r* (T2)** | ***r* (T3)** | ***r* (T1)** | ***r* (T2)** | ***r* (T3)** |
| **SMU intensity** | 0.306*** | 0.158** | 0.056 | | | | | | |
| **Depressive symptoms** | 0.324*** | 0.142*** | 0.055 | 0.152* | 0.056 | 0.001 | | | |
| **Cybervictimization** | 0.297*** | 0.145*** | 0.052 | 0.187*** | 0.081 | 0.027 | 0.272*** | 0.114* | 0.049 |
| **M1d** | **SMU problems** | | | **SMU intensity** | | | **Depressive symptoms** | | |
| | ***r* (T1)** | ***r* (T2)** | ***r* (T3)** | ***r* (T1)** | ***r* (T2)** | ***r* (T3)** | ***r* (T1)** | ***r* (T2)** | ***r* (T3)** |
| **SMU intensity** | 0.306*** | 0.158** | 0.056 | | | | | | |
| **Depressive symptoms** | 0.338*** | 0.138*** | 0.055 | 0.152* | 0.055 | 0.000 | | | |
| **Subjective school achievements** | -0.103** | -0.027 | -0.024 | -0.116** | -0.060 | -0.011 | -0.067 | -0.068 | -0.047 |
| **M1e** | **SMU problems** | | | **SMU intensity** | | | **Depressive symptoms** | | |
| | ***r* (T1)** | ***r* (T2)** | ***r* (T3)** | ***r* (T1)** | ***r* (T2)** | ***r* (T3)** | ***r* (T1)** | ***r* (T2)** | ***r* (T3)** |
| **SMU intensity** | 0.305*** | 0.161** | 0.057 | | | | | | |
| **Depressive symptoms** | 0.329*** | 0.137*** | 0.055 | 0.152* | 0.057 | 0.000 | | | |
| **Face-to-face contact** | 0.071* | 0.003 | 0.005 | 0.195*** | 0.117* | -0.10 | 0.021 | -0.031 | -0.022 |

*Notes*. RI-CLPM = random intercept cross-lagged panel model. SMU = social media use; β = STDYX-standardized; SE = standard error. Results in table show the average estimates over 20 imputed datasets of plausible values. T1 estimates are correlations. T2 and T3 estimates are residual correlations.
*** $p$ < 0.001; ** $p$ < 0.01; * $p$ < 0.05.

**Table A6.4**

*RI-CLPMs on Life Satisfaction Within-Person (Residual) Correlations Within Same Year (n = 2,109)*

| **M2b** | **SMU problems** | | | **SMU intensity** | | | **Life satisfaction** | | |
|---|---|---|---|---|---|---|---|---|---|
| | ***r* (T1)** | ***r* (T2)** | ***r* (T3)** | ***r* (T1)** | ***r* (T2)** | ***r* (T3)** | ***r* (T1)** | ***r* (T2)** | ***r* (T3)** |
| **SMU intensity** | 0.305*** | 0.157** | 0.057 | | | | | | |
| **Life satisfaction** | -0.224*** | -0.135** | -0.045 | -0.089 | -0.023 | 0.000 | | | |
| **Upward social comparisons** | 0.305*** | 0.162*** | 0.057 | 0.169*** | 0.073 | -0.010 | -0.169** | -0.172** | -0.034 |
| **M2c** | **SMU problems** | | | **SMU intensity** | | | **Life satisfaction** | | |
| | ***r* (T1)** | ***r* (T2)** | ***r* (T3)** | ***r* (T1)** | ***r* (T2)** | ***r* (T3)** | ***r* (T1)** | ***r* (T2)** | ***r* (T3)** |
| **SMU intensity** | 0.307*** | 0.157** | 0.056 | | | | | | |
| **Life satisfaction** | -0.223*** | -0.138** | -0.046 | -0.086 | -0.022 | 0.000 | | | |
| **Cybervictimization** | 0.297*** | 0.149*** | 0.050 | 0.186** | 0.081 | 0.027 | -0.203*** | -0.105 | -0.031 |
| **M2d** | **SMU problems** | | | **SMU intensity** | | | **Life satisfaction** | | |
| | ***r* (T1)** | ***r* (T2)** | ***r* (T3)** | ***r* (T1)** | ***r* (T2)** | ***r* (T3)** | ***r* (T1)** | ***r* (T2)** | ***r* (T3)** |
| **SMU intensity** | 0.307*** | 0.157** | 0.056 | | | | | | |
| **Life satisfaction** | -0.226*** | -0.135** | -0.047 | -0.090 | -0.022 | -0.002 | | | |
| **Subjective school achievements** | -0.101** | -0.029 | -0.024 | -0.114* | -0.060 | -0.012 | 0.111* | 0.121** | 0.041 |
| **M2e** | **SMU problems** | | | **SMU intensity** | | | **Life satisfaction** | | |
| | ***r* (T1)** | ***r* (T2)** | ***r* (T3)** | ***r* (T1)** | ***r* (T2)** | ***r* (T3)** | ***r* (T1)** | ***r* (T2)** | ***r* (T3)** |
| **SMU intensity** | 0.306*** | 0.159** | 0.057 | | | | | | |
| **Life satisfaction** | -0.226*** | -0.136** | -0.046 | -0.085 | -0.026 | -0.001 | | | |
| **Face-to-face contact** | 0.073* | 0.004 | 0.004 | 0.197*** | 0.119* | -0.009 | 0.095 | 0.179*** | 0.065 |

*Notes.* RI-CLPM = random intercept cross-lagged panel model. SMU = social media use; β = STDYX-standardized; SE = standard error. Results in table show the average estimates over 20 imputed datasets of plausible values. T1 estimates are correlations. T2 and T3 estimates are residual correlations.
*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

**Table A6.5**

*RI-CLPMs on Depressive Symptoms Extended With Mediators, Within-Person (Cross-)Lagged Associations by Gender ($n_{boys}$ = 1,203 $n_{girls}$ = 906)*

| **M1b** | **SMU problems T2** | | **SMU intensity T2** | | **Depressive symptoms T2** | | **Upward social comparisons T2** | |
|---|---|---|---|---|---|---|---|---|
| | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ |
| **SMU problems T1** | 0.692*** | 0.684*** | 0.151** | 0.222* | 0.163* | 0.194* | 0.206** | 0.249** |
| **SMU intensity T1** | 0.069 | 0.107* | 0.354** | 0.278 | -0.023 | 0.012 | 0.046 | 0.007 |
| **Depressive symptoms T1** | 0.050 | 0.056 | -0.018 | 0.022 | 0.194 | 0.303 | 0.041 | 0.104 |
| **Upward social comparisons T1** | 0.039 | 0.042 | 0.049 | 0.002 | 0.009 | 0.016 | 0.001 | 0.012 |
| | **SMU problems T3** | | **SMU intensity T3** | | **Depressive symptoms T3** | | **Upward social comparisons T3** | |
| | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ |
| **SMU problems T2** | 0.739*** | 0.746*** | 0.203* | 0.302* | 0.081 | 0.084 | 0.135* | 0.179* |
| **SMU intensity T2** | 0.022 | 0.033 | 0.403* | 0.326 | 0.002 | -0.029 | 0.036 | -0.042 |
| **Depressive symptoms T2** | 0.014 | 0.020 | -0.010 | -0.034 | 0.370*** | 0.432*** | 0.045 | 0.024 |
| **Upward social comparisons T2** | 0.013 | 0.018 | 0.024 | -0.028 | 0.018 | 0.038 | 0.109 | 0.097 |
| **M1c** | **SMU problems T2** | | **SMU intensity T2** | | **Depressive symptoms T2** | | **Cybervictimization T2** | |
| | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ |
| **SMU problems T1** | 0.685*** | 0.694*** | 0.153** | 0.227* | 0.161* | 0.196 | 0.173** | 0.189* |
| **SMU intensity T1** | 0.065 | 0.108* | 0.358** | 0.281 | -0.033 | 0.015 | 0.126 | 0.094 |
| **Depressive symptoms T1** | 0.048 | 0.060 | -0.019 | 0.029 | 0.198 | 0.310 | -0.032 | 0.103 |
| **Cybervictimization T1** | 0.061 | 0.008 | 0.032 | -0.022 | 0.013 | 0.004 | 0.177 | 0.128 |
| | **SMU problems T3** | | **SMU intensity T3** | | **Depressive symptoms T3** | | **Cybervictimization T3** | |
| | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ |
| **SMU problems T2** | 0.739*** | 0.748*** | 0.189* | 0.293* | 0.101 | 0.087 | 0.171** | 0.142 |
| **SMU intensity T2** | 0.022 | 0.032 | 0.403* | 0.322 | 0.007 | -0.027 | 0.061 | -0.010 |
| **Depressive symptoms T2** | 0.015 | 0.022 | -0.017 | -0.039 | 0.379*** | 0.441*** | -0.030 | 0.015 |
| **Cybervictimization T2** | 0.010 | 0.010 | 0.070 | 0.010 | -0.060 | 0.014 | 0.103 | 0.080 |
| **M1d** | **SMU problems T2** | | **SMU intensity T2** | | **Depressive symptoms T2** | | **Subjective school achievements T2** | |
| | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ |
| **SMU problems T1** | 0.700*** | 0.696*** | 0.157** | 0.218* | 0.169* | 0.197 | -0.018 | -0.066 |
| **SMU intensity T1** | 0.071 | 0.107* | 0.362** | 0.275 | -0.029 | 0.009 | -0.112 | -0.036 |
| **Depressive symptoms T1** | 0.054 | 0.060 | -0.014 | 0.019 | 0.197 | 0.300 | 0.013 | -0.035 |
| **Subj. school achievements T1** | -0.004 | 0.000 | -0.039 | -0.050 | 0.019 | -0.051 | 0.262*** | 0.321*** |
| | **SMU problems T3** | | **SMU intensity T3** | | **Depressive symptoms T3** | | **Subjective school achievements T3** | |
| | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ |
| **SMU problems T2** | 0.742*** | 0.750*** | 0.202* | 0.286* | 0.086 | 0.092 | -0.054 | -0.080 |
| **SMU intensity T2** | 0.023 | 0.033 | 0.406* | 0.331 | 0.004 | -0.026 | -0.057 | 0.013 |
| **Depressive symptoms T2** | 0.018 | 0.024 | -0.014 | -0.039 | 0.375*** | 0.442*** | 0.007 | -0.060 |
| **Subj. school achievements T2** | 0.012 | -0.007 | -0.069 | -0.030 | 0.027 | 0.003 | 0.066 | 0.095 |
| **M1e** | **SMU Problems T2** | | **SMU intensity T2** | | **Depressive symptoms T2** | | **Face-to-face contact T2** | |
| | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ |
| **SMU problems T1** | 0.700*** | 0.696*** | 0.161** | 0.223* | 0.169* | 0.198* | 0.044 | 0.025 |
| **SMU intensity T1** | 0.075 | 0.106* | 0.348** | 0.263 | -0.027 | 0.025 | 0.058 | 0.100 |
| **Depressive symptoms T1** | 0.054 | 0.060 | -0.014 | 0.024 | 0.197 | 0.310 | 0.006 | -0.062 |
| **Face-to-face contact T1** | -0.014 | 0.011 | 0.036 | 0.079 | -0.013 | -0.047 | 0.265* | 0.303* |
| | **SMU problems T3** | | **SMU intensity T3** | | **Depressive symptoms T3** | | **Face-to-face contact T3** | |
| | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ |
| **SMU problems T2** | 0.742*** | 0.751*** | 0.209* | 0.289* | 0.084 | 0.093 | 0.060 | 0.035 |
| **SMU intensity T2** | 0.022 | 0.035 | 0.401* | 0.323 | 0.003 | -0.025 | 0.014 | 0.007 |
| **Depressive symptoms T2** | 0.017 | 0.023 | -0.008 | -0.032 | 0.373*** | 0.439*** | -0.023 | -0.026 |
| **Face-to-face contact T2** | 0.002 | -0.012 | 0.013 | 0.046 | 0.008 | -0.023 | 0.409*** | 0.374** |

*Notes.* RI-CLPM = random intercept cross-lagged panel model. SMU = social media use; $\beta$ = STDYX-standardized. Results in table show the average estimates over 20 imputed datasets of plausible values. All models included (residual) correlations between measurements in the same year. Observed differences between boys and girls were all not significant ($p > 0.05$).
*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

**Table A6.6**

*RI-CLPMs on Life Satisfaction Extended With Mediators, Within-Person (Cross-)Lagged Associations by Gender ($n_{boys}$ = 1,203 $n_{girls}$ = 906)*

| **M2b** | **SMU problems T2** | | **SMU intensity T2** | | **Life satisfaction T2** | | **Upward social comparisons T2** | |
|---|---|---|---|---|---|---|---|---|
| | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ |
| **SMU problems T1** | 0.695*** | 0.692*** | 0.145** | 0.222* | -0.121* | -0.198* | 0.212** | 0.261** |
| **SMU intensity T1** | 0.069 | 0.108* | 0.353** | 0.283 | -0.028 | 0.033 | 0.047 | 0.005 |
| **Life satisfaction T1** | -0.053 | -0.034 | -0.018 | -0.021 | 0.089 | 0.054 | -0.033 | -0.051 |
| **Upward social comparisons T1** | 0.045 | 0.049 | 0.044 | -0.001 | -0.022 | -0.083 | 0.003 | 0.033 |
| | **SMU problems T3** | | **SMU intensity T3** | | **Life satisfaction T3** | | **Upward social comparisons T3** | |
| | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ |
| **SMU problems T2** | 0.740*** | 0.753*** | 0.197* | 0.303 | -0.087 | -0.160 | 0.142** | 0.181* |
| **SMU intensity T2** | 0.022 | 0.032 | 0.402* | 0.332 | -0.038 | 0.011 | 0.035 | -0.041 |
| **Life satisfaction T2** | -0.007 | -0.001 | -0.028 | 0.075 | 0.113 | 0.107 | -0.025 | -0.011 |
| **Upward social comparisons T2** | 0.014 | 0.021 | 0.018 | -0.020 | -0.024 | 0.038 | 0.112 | 0.101 |
| **M2c** | **SMU problems T2** | | **SMU intensity T2** | | **Life satisfaction T2** | | **Cybervictimization T2** | |
| | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ |
| **SMU problems T1** | 0.689*** | 0.703*** | 0.148** | 0.228* | -0.134* | -0.203** | 0.177** | 0.206** |
| **SMU intensity T1** | 0.066 | 0.108* | 0.356** | 0.286 | -0.025 | 0.034 | 0.118 | 0.093 |
| **Life satisfaction T1** | -0.052 | -0.038 | -0.014 | -0.030 | 0.097 | 0.060 | 0.081 | -0.057 |
| **Cybervictimization T1** | 0.064 | 0.014 | 0.027 | -0.028 | 0.029 | -0.077 | 0.183 | 0.130 |
| | **SMU problems T3** | | **SMU intensity T3** | | **Life satisfaction T3** | | **Cybervictimization T3** | |
| | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ |
| **SMU problems T2** | 0.741*** | 0.755*** | 0.182* | 0.296 | -0.108 | -0.147 | 0.168** | 0.150 |
| **SMU intensity T2** | 0.021 | 0.033 | 0.400* | 0.329 | -0.040 | 0.009 | 0.060 | -0.011 |
| **Life satisfaction T2** | -0.009 | -0.003 | -0.023 | 0.077 | 0.124 | 0.109 | 0.025 | 0.008 |
| **Cybervictimization T2** | 0.011 | 0.013 | 0.066 | 0.010 | 0.052 | -0.002 | 0.105 | 0.077 |
| **M2d** | **SMU problems T2** | | **SMU intensity T2** | | **Life satisfaction T2** | | **Subjective school achievements T2** | |
| | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ |
| **SMU problems T1** | 0.706*** | 0.706*** | 0.152** | 0.218* | -0.127** | -0.213** | -0.015 | -0.076 |
| **SMU intensity T1** | 0.072 | 0.108* | 0.359** | 0.280 | -0.025 | 0.033 | -0.111 | -0.035 |
| **Life satisfaction T1** | -0.056 | -0.037 | -0.017 | -0.020 | 0.085 | 0.070 | -0.013 | 0.007 |
| **Subj. school achievements T1** | 0.001 | -0.004 | -0.037 | -0.046 | 0.031 | 0.077 | 0.263*** | 0.320*** |
| | **SMU problems T3** | | **SMU intensity T3** | | **Life satisfaction T3** | | **Subjective school achievements T3** | |
| | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ |
| **SMU problems T2** | 0.744*** | 0.757*** | 0.196* | 0.290 | -0.094 | -0.143 | -0.054 | -0.097 |
| **SMU intensity T2** | 0.023 | 0.033 | 0.403* | 0.337 | -0.041 | 0.011 | -0.057 | 0.013 |
| **Life satisfaction T2** | -0.012 | -0.004 | -0.024 | 0.078 | 0.120 | 0.101 | -0.011 | 0.004 |
| **Subj. school achievements T2** | 0.012 | -0.007 | -0.066 | -0.032 | -0.021 | 0.054 | 0.068 | 0.099 |
| **M2e** | **SMU Problems T2** | | **SMU intensity T2** | | **Life satisfaction T2** | | **Face-to-face contact T2** | |
| | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ |
| **SMU problems T1** | 0.706*** | 0.706*** | 0.154** | 0.223* | -0.133** | -0.220** | 0.048 | 0.032 |
| **SMU intensity T1** | 0.075 | 0.108* | 0.347** | 0.267 | -0.040 | 0.018 | 0.059 | 0.101 |
| **Life satisfaction T1** | -0.054 | -0.039 | -0.024 | -0.025 | 0.082 | 0.075 | 0.008 | 0.096 |
| **Face-to-face contact T1** | -0.006 | 0.009 | 0.038 | 0.079 | 0.080 | 0.050 | 0.259* | 0.304* |
| | **SMU problems T3** | | **SMU intensity T3** | | **Life satisfaction T3** | | **Face-to-face contact T3** | |
| | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ | $\beta_{boys}$ | $\beta_{girls}$ |
| **SMU problems T2** | 0.743*** | 0.759*** | 0.200* | 0.294* | -0.092 | -0.149 | 0.051 | 0.037 |
| **SMU intensity T2** | 0.022 | 0.036 | 0.398* | 0.329 | -0.043 | 0.004 | 0.014 | 0.011 |
| **Life satisfaction T2** | -0.012 | -0.002 | -0.036 | 0.073 | 0.118 | 0.103 | -0.020 | 0.045 |
| **Face-to-face contact T2** | 0.005 | -0.015 | 0.018 | 0.037 | 0.004 | 0.049 | 0.410*** | 0.369** |

*Notes.* RI-CLPM = random intercept cross-lagged panel model. SMU = social media use; β = STDYX-standardized. Results in table show the average estimates over 20 imputed datasets of plausible values. All models included (residual) correlations between measurements in the same year. Observed differences between boys and girls were all not significant ($p$ > 0.05).
*** $p$ < 0.001; ** $p$ < 0.01; * $p$ < 0.05.

# CHAPTER 7

# THE COURSE OF PROBLEMATIC SOCIAL MEDIA USE IN YOUNG ADOLESCENTS: A LATENT CLASS GROWTH ANALYSIS

Maartje Boer, Gonneke W. J. M. Stevens, Catrin Finkenauer, and Regina J. J. M. van den Eijnden

**Author Contributions**

All authors conceived of the study. MB conducted the literature review, data analyses, and drafted the initial and revised manuscript. RvdE initiated and coordinated the data collection of the data from the present study. GS, CF, and RvdE critically reviewed all sections of the initial and revised manuscript and advised during all stages of the manuscript preparation. All authors approved of the final manuscript.

**Publication**

Boer, M., Stevens, G. W. J. M., Finkenauer, C., De Looze, M. E., & Van den Eijnden, R. J. J. M. (2021). The course of problematic social media use in young adolescents: A latent class growth analysis. *Child Development (in press)*. https://doi.org/10.1111/cdev.13712

# Abstract

Using four waves of longitudinal data collected in 2015-2019 from 1,419 adolescents ($M_{age}$ = 12.5, 45.9% female, 21.9% immigrant), this study identified trajectories of problematic social media use (SMU) in parallel with trajectories of SMU frequency. Latent class growth analysis identified two subgroups with relatively high levels of problematic SMU over time, of which one showed high (24.7%) and one showed average SMU frequency (15.8%), and two subgroups with persistently low levels of problematic SMU, of which one reported low (22.4%) and one reported high SMU frequency (37.1%). Although both subgroups with higher levels of problematic SMU reported low subjective wellbeing, the group with high SMU frequency showed low self-control, whereas the group with average SMU frequency reported poor social competencies.


*Keywords*: Problematic social media use, social media addiction, wellbeing, adolescents, growth trajectories.

# The Course of Problematic Social Media Use in Young Adolescents: A Latent Class Growth Analysis

The current generation of young adolescents grow up in a 'hybrid' world, where their offline world is intertwined with online contexts that are facilitated by social media, such as Instagram and Snapchat. Between 2017 and 2019, 63% of 12- to 14-year-old and 77% of 15- and 16-year-old European adolescents reported daily usage of social media (Smahel et al., 2020). Other research shows that in 2017 and 2018, a large share of 13- and 15-year-old European adolescents reported that they were interacting online with friends and others almost all the time throughout the day (36% and 41%, respectively) (Inchley et al., 2020b). From a developmental perspective, it is understandable why social media are so popular among early and middle adolescents (Granic et al., 2020). Social media allow young adolescents to form and maintain peer relationships (e.g., through instant messaging), to share their perspectives, narratives, and self-portrayals with others (e.g., by uploading personal photos, videos, and texts), to receive feedback on their appearances and online behaviors (e.g., through 'likes' and responses from peers), and to learn from others (e.g., by browsing through peers' uploads). These functions are all crucial for identity development: a core developmental task of young adolescents (Erikson, 1968).

However, for some of adolescents, social media use (SMU) deviates from normative adolescent behavior, namely when they experience symptoms of addiction to social media. In that case, adolescents cannot regulate their SMU: They have social media on top of their mind constantly, feel stress or anxiety when SMU is not possible, and/or report that their SMU interferes with their functioning in important life domains (Andreassen, 2015; Griffiths et al., 2014). The presence of such addiction symptoms is considered harmful (Griffiths et al., 2014). For instance, meta-analytic findings indicate that adolescents with such symptoms report low wellbeing (Marino et al., 2018b). Furthermore, several longitudinal studies, including studies based on data from the present study, suggest that symptoms of addiction towards SMU increase mental health problems, such as depressive symptoms, psychological distress, and attention deficits (Boer, Stevens, et al., 2020; Boer, Stevens, Finkenauer, De Looze, et al., 2021; I. H. Chen et al., 2020; Raudsepp, 2019). Nevertheless, social media addiction has not been acknowledged as such in any diagnostic manual, such as the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) (American Psychiatric Association, 2013). Therefore, we refer to it as problematic SMU (Lee et al., 2017).

Research in 29 countries showed that in 2017 and 2018, 7% of 11- to 15-year-olds reported high levels of problematic SMU (Boer, Van den Eijnden, et al., 2020). Despite the growing literature on predictors and outcomes of problematic SMU, studies have not investigated how problematic SMU evolves over time. Consequently, it is unclear whether and for whom problematic SMU persists, increases, or decreases over time. The present study addresses this gap using four annual waves of longitudinal data among Dutch young adolescents. It aims to identify trajectories of problematic SMU and to investigate predictors of these trajectories. Establishing when, to what extent, and among whom problematic SMU emerges identifies windows of opportunity for the development of prevention and intervention programs on problematic SMU. Specifically, it identifies at which period in adolescence the implementation of such programs would be relevant and to whom these programs may be most valuable. Such programs may be important, given the increasing evidence that problematic users face several risks related to their mental health (Boer, Stevens, Finkenauer, De Looze, et al., 2021; I. H. Chen et al., 2020; Raudsepp, 2019).

## Trajectories of Problematic SMU

To our knowledge, there is currently no theoretical basis and empirical evidence on the course of problematic SMU throughout adolescence, or other behaviors that, similar to problematic SMU, can be characterized as behavioral addictions. As such, hypotheses on how adolescents' level of problematic SMU develops over time have not yet been advanced. To understand how problematic SMU may evolve, it is important to consider the conceptualization of the behavior: problematic SMU is characterized by addiction-like behaviors that are rather exceptional among adolescents (Griffiths, 2013), and can therefore be regarded as deviant behavior. The behavior is conceptually different from (highly) frequent SMU, that is regarded as normative adolescent behavior nowadays. While many adolescents show high SMU frequency (Anderson & Jiang, 2018), this does not necessarily imply loss of control over SMU, which is central to problematic SMU. Furthermore, cross-sectional as well as longitudinal research shows that problematic SMU is related to lower mental health, while high SMU frequency is not (Boer, Stevens, Finkenauer, De Looze, et al., 2021; Boer, Van den Eijnden, et al., 2020; Shensa et al., 2017). Hence, we pose that problematic SMU reflects deviant behavior that is related to mental health problems.

Therefore, to understand how problematic SMU potentially develops over time, research on adolescents' developmental trajectories of other deviant behaviors and mental health may provide some directions. Research consistently shows heterogeneous developmental trajectories of, for example, depressive symptoms (Dekker et al., 2007), aggression (Bongers et al., 2004), delinquency (Reinecke, 2006a), and binge drinking (Chassin et al., 2002). Together, these studies broadly suggest that adolescents' vulnerability to problems typically develops through multiple pathways throughout adolescence: One trajectory concerns adolescents who show no or little vulnerability to a specific problem (i.e., persistent low risk), another trajectory concerns adolescents who show relatively persistent high vulnerability to a problem (i.e., persistent high risk), and at least one trajectory concerns adolescents who show variation in problems over time (e.g., temporal, decreasing, or increasing risk). The number and shape(s) of such variable trajectories differs across studies, suggesting that the variability depends on the type of problem investigated. Considering problematic SMU as a deviant behavior that is related to low mental health, adolescents' development of problematic SMU may parallel these broad patterns of trajectories, including a more persistent low- and high risk, and one or multiple variable trajectories. Given the possible detrimental impact of problematic SMU (e.g., Chen et al., 2020; Raudsepp, 2019), it is particularly important to investigate whether and which adolescents experience high levels of problematic SMU persistently and thus experience prolonged risks to their mental health throughout their development.

So far, only large-scale cross-sectional studies reporting on the average association between age and problematic SMU shed some light on the course of problematic SMU. While some studies show that problematic SMU was more prevalent among older youth (Boer, Van den Eijnden, et al., 2020; Müller et al., 2016), other studies suggest that this was more prevalent among younger youth (Mérelle et al., 2017; Wartberg et al., 2020), and others show no age differences (Bányai et al., 2017; Ho et al., 2017). A possible explanation for these inconclusive findings is that there are subgroups of adolescents with different trajectories of problematic SMU, and that these subgroups were unevenly represented in the samples of previous studies.

## Predictors of Problematic SMU

It has been proposed that adolescents with low *subjective wellbeing* and poor *social competencies*, such as low life satisfaction, low self-esteem, and poor competencies to form and maintain friendships, are sensitive to problematic SMU. SMU may be especially appealing for adolescents with these psychosocial vulnerabilities, because other than in offline encounters, online they can easily present themselves in a positive way. Consequently, they may develop a preference for online interaction over face-to-face and maladaptive cognitions about social media, such as the perception to only have a meaningful life on social media, which may lead to problematic SMU (Caplan, 2003; Davis, 2001). In addition, adolescents with low *self-control*, indicated by attention deficits or impulsivity, have limited ability to inhibit immediate impulses. Therefore, they may not be able to resist temptations and to regulate their SMU, which may make them sensitive to problematic SMU (Mérelle et al., 2017; Wu et al., 2013). However, these propositions lack a developmental perspective, because they do not describe how these psychosocial factors relate to *trajectories* of problematic SMU. That is, whether they increase the risk of, for example, persistently or temporarily high levels of problematic SMU. Identifying which psychosocial profiles increase the risk of following specific trajectories of problematic SMU may support the development of intervention and prevention programs aimed at problematic SMU that target adolescents' vulnerabilities. These programs are considered particularly relevant for those youth whose high levels of problematic SMU do not desist.

Longitudinal research, under which studies that used data from the present study, examined associations between some of the abovementioned psychosocial factors and problematic SMU (Boer, Stevens, et al., 2020; Boer, Stevens, Finkenauer, De Looze, et al., 2021; Du et al., 2021; Li et al., 2018). Although these studies provided insight into the average association between psychosocial characteristics and problematic SMU over time, they did not explore whether these factors predict distinct trajectories of problematic SMU. For example, low subjective wellbeing may underlie specific trajectories of problematic SMU, but not others. Furthermore, these studies typically focused on predictors of *changes* in problematic SMU, which do not allow for establishing predictors of persistent levels of problematic SMU.

## Current Study

Social media are ubiquitous in the daily lives of contemporary adolescents and likely play a significant role in the individual development of particularly young adolescents. Such a context, where social media are omnipresent, may make some adolescents susceptible to developing problematic SMU, which are characterized by symptoms of addiction. Using four waves of longitudinal data with yearly time intervals among Dutch adolescents in early and middle adolescence ($M_{age}$ = 12.511, $SD_{age}$ = 0.602 in the first wave), this study firstly aimed to explore how adolescents' level of problematic SMU evolved over time. Based on prior studies on the development of various types of problems during adolescence, we expected to find a persistent low- and a high-risk trajectory, and at least one more variable trajectory of problematic SMU. To consolidate our suggestion that problematic SMU differs from the frequency of SMU and illuminate the similarities or differences between their trajectories, we investigated adolescents' trajectories of problematic SMU in parallel with their trajectories of SMU frequency. The second aim was to investigate to what extent subjective wellbeing (life satisfaction and self-esteem), low self-control (attention deficit and impulsivity), and social competencies predicted the identified trajectories. Although research showed that these psychosocial characteristics are related with problematic SMU, their role in particular developments of problematic SMU remains unexplored. Therefore, we did not establish a priori expectations regarding their predictive role in specific trajectories. Thus, given the data-driven approach to identify trajectories of problematic SMU and its predictors, the design of the present study was considered exploratory.

# Methods

## Sample

Data came from the Digital Youth project: a longitudinal study among students assessing self-report internet-related behaviors and wellbeing (Van den Eijnden et al., 2018). Students were recruited through schools in urban and suburban areas in the Netherlands. Schools were selected based on the project initiator's personal network of contacts with key persons in schools. The data include five waves of data with yearly time intervals, conducted in February-April of 2015 until 2019. In each survey round, students from previous round(s) were invited to participate, but also new students from different grades entered. For the present study, we selected four waves of data from students enrolled in 7$^{th}$ grade at time of the 2015 or 2016 survey rounds, which yielded two subsets: students sampled from 2015 to 2018 ($n$ = 1,352) and students sampled from 2016 to 2019 ($n$ = 998). The two subsets were merged, such that each subset consisted of four waves that we refer to as T1 to T4. Hence, growth was modelled as a function of students' grade, whereby all students were enrolled in 7$^{th}$ grade at T1 and in 10$^{th}$ grade at T4. Students who repeated a class ($n$ = 46) or who participated in less than two waves ($n$ = 885) were excluded, yielding an analysis sample of 1,419 included students. Excluded students reported higher levels of problematic SMU, lower life satisfaction, higher impulsivity, and poorer social competencies than included students, but with small effect sizes (Cohen's $D$ = 0.114 to 0.216). Also, the proportion of boys, adolescents attending pre-vocational education, and adolescents with an immigrant background was higher among the sample of excluded students, although these differences were very small (Cramer's $V$ = 0.064 to 0.109).

There were few differences between the two subsets from the analysis sample: Adolescents in the second subset reported higher levels of problematic SMU, but also higher life satisfaction than adolescents in the first subset, although these differences were small (Cohen's $D$ = 0.171 and 0.131, respectively). Additionally, the proportion of adolescents attending pre-vocational education was highest in the second subset, although here too, the difference was small (Cramer's $V$ = 0.137). Despite these small differences, we found that the (variances of the) initial level and development of problematic

SMU and SMU frequency did not vary across the two subsets, suggesting that the distributions of the trajectories were comparable (Appendix, Table A7.1). Hence, merging the two samples was justified.

Within the analysis sample, students were on average 12.511 years old (*SD* = 0.602) in T1, 45.9% was girl, and 21.9% had an immigrant background. Among adolescents with an immigrant background, 45.2% had one parent that was born in Suriname, Netherlands Antilles, Morocco, Turkey, or another country, and their other parent was born in the Netherlands. The other 54.8% had two parents from these or other countries. In addition, students followed different educational tracks according to the Dutch education system, namely pre-vocational (*VMBO;* 57.8%), intermediate (*HAVO;* 28.5%), and pre-university (*VWO;* 13.7%). The present sample composition differed somewhat from the Dutch school population with respect to educational level: 13.7% among sample participants versus 20.6% in the Dutch 10$^{th}$-grade population in 2018/2019 (Central Bureau for Statistics, 2021).



Participation rates at T1 until T4 were 55.1%, 93.5%, 75.9%, and 34.9%, respectively. The reason why data were not complete in T1 was because some students' first participation was in T2 or T3. Nevertheless, all students were enrolled in the same grade at each assessment. There was considerable dropout among students attending pre-vocational education: Of all adolescents participating in T4, 19.6% was pre-vocational student, while of all adolescents participating in T1, this was 60.6%. This dropout was mainly due to dropout of entire pre-vocational schools, school years (e.g., final exam years), or school classes (e.g., because teachers were not able to schedule the survey assessment), and not due to individual selection.

Prior to each survey assessment, parents received a letter which informed them about the study and provided them with the opportunity to refuse participation of their child via email or telephone call. Also, prior to each survey round, students were informed about the purpose of the study, that participation was voluntary and anonymous, and that they could withdraw their participation at any moment. Both parents and students received this information two weeks before the first day of data collection. The assessments were administered in the classroom through digital self-completion, whereby research-assistant monitored and assisted students where necessary. The assessments were carried out in accordance with the

Declaration of Helsinki and the study procedure was approved by the board of ethics of Utrecht University (FETC16-076 Eijnden).

## Measures

### *Problematic SMU*

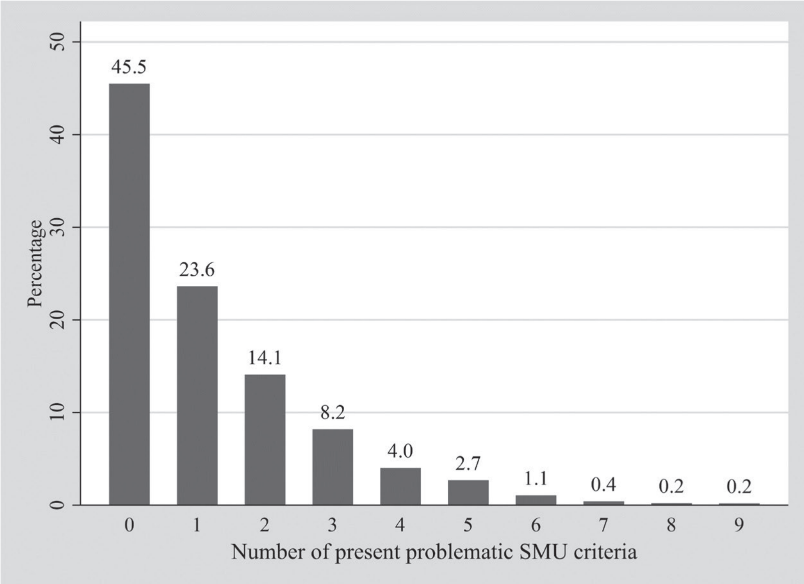
We used the 9-item Social Media Disorder-Scale to measure problematic SMU, that measures nine symptoms of addiction to social media, including preoccupation, withdrawal, tolerance, persistence, displacement, conflict, deception, escape, and problems (Van den Eijnden et al., 2016). Respondents were asked, for example, whether in the past year they regularly could not think of anything else but the moment to use social media again (i.e., preoccupation), with a dichotomous response scale (1 *yes* or 0 *no*). The scale corresponds to the nine diagnostic criteria for internet gaming disorder according to the appendix of the DSM-5, which also follow a dichotomous response structure (American Psychiatric Association, 2013; Lemmens et al., 2015). A sum-score was computed that denotes the number of present criteria. Higher sum-scores are thereby interpreted as higher levels of problematic SMU. This sum-score followed a Poisson distribution (Figure 7.1), corresponding to the distribution observed in a nationally representative sample of 6,266 Dutch students aged 12 to 16 (Boer, Stevens, Finkenauer, Koning, et al., 2021). Thus, high levels of problematic SMU are rather exceptional in the adolescent population, given that most adolescents do not report any problems, whereas a small minority report many. The scale has been found to provide appopriate criterion validity: The higher the level of problematic SMU, the higher the probability of reporting problems related to mental health, school, and sleep, whereby moderate levels of problematic SMU (i.e., endorsement of two to five problematic SMU criteria) are already indicative of a higher risk of problems (Boer, Stevens, Finkenauer, Koning, et al., 2021). As appropriate for dichotomous variables, reliability was calculated using the tetrachoric correlation matrix (Gadermann et al., 2012), yielding an ordinal alpha ranging from 0.834 to 0.856 at all waves.

### *SMU Frequency*

Four items assessed respondents' SMU frequency (Boer, Stevens, et al., 2020).

**Figure 7.1**

*Distribution of Problematic SMU*




*Notes.* SMU = social media use. The distribution was derived from the complete data on problematic SMU with the data in long format (*n* = 3,675 out of 5,676 observations).



Respondents were asked how many times per *day* they viewed, per *week* they 'liked', and per *week* they responded to messages, photos, or videos of others on social network sites, such as Facebook, Twitter, Instagram, Google+, or Pinterest (1 *never or less than once* to 7 *more than 40 times*). Respondents were also asked how many times per *day* they send a message, photo, or video via their smartphone via for example WhatsApp, Chat, SnapChat or SMS (1 *less than once* to 7 *more than 80 times*). Scores on the four items were averaged, such that the score denoted respondents' mean level of SMU frequency. Cronbach's alpha ranged between 0.781 and 0.853 across all waves. The original scale includes additional items on the frequency of posting a message, photo, or video on social network sites and checking the smartphone for incoming messages, photos, or videos. Of these two items, the first was excluded because it had a low factor loading (< 0.500) and the second because removal yielded substantial model fit improvement due to high overlap with the other item on smartphone use (*r* = 0.674 to 0.709).

### *Subjective Wellbeing*

The first indicator of subjective wellbeing was *life satisfaction*, using the 7-item Student's Life Satisfaction Scale (Huebner, 1991). Respondents were asked about their thoughts around their own life, for example whether they think that their life is going well (1 *strongly disagree* to 6 *strongly agree*). The second indicator was *self-esteem,* using 5 items of the Rosenberg Self-esteem Scale (Rosenberg, 1965). Respondents were asked, for example, whether they felt that they have a number of good qualities (1 *strongly disagree* to 5 *strongly agree*). Both scales have been validated among adolescents extensively and adopted in translated form in many adolescent surveys worldwide (Butler & Gasson, 2005; Proctor et al., 2009). For both subjective wellbeing indicators, we computed mean scores of the items. Across all waves, Cronbach's alpha for life satisfaction and self-esteem ranged from 0.809 to 0.838 and from 0.777 to 0.825, respectively.

### *Self-Control*

The first indicator of self-control was *attention deficit,* measured with a 9-item subscale from the Attention Deficit Hyperactivity Disorder (ADHD)-Questionnaire (Scholte & Van der Ploeg, 1999). Respondents were asked, for example, how often they experience difficulties in sustaining prolonged attention on tasks or activities (1 *never* to 5 *very often*). The second indicator was *impulsivity*, measured with a 6-item subscale from the ADHD-Questionnaire. Respondents were asked, for example, how often they find it difficult to wait for their turn (1 *never* to 5 *very often*). The ADHD-Questionnaire has been shown to be a reliable and valid measure of ADHD in Dutch adolescents (Scholte & Van der Ploeg, 1999). For both attention deficit and impulsivity, we calculated mean scores using the subscale items. Cronbach's alpha for attention deficit and impulsivity ranged from 0.860 to 0.882 and 0.786 to 0.834, respectively.

### *Social Competencies*

We used *perceived friendship competence* as indicator for social competencies, measured with the 5-item 'close friendship'-subscale of the Self-Perception Profile for Adolescents (Harter, 2012; Straathof & Treffers, 1989). The subscale has been shown to provide reliable test scores in several adolescent populations (E. Rose et al., 2012). We used a modified Dutch version of the subscale (Straathof & Treffers, 1989), whereby respondents were asked, for example, whether they find it difficult to form friendships to which they can count on (1 *strongly disagree* to 5 *strongly agree*). Scores were recoded such that high values indicate high levels of social competencies, after which mean scores were computed. Cronbach's alpha ranged from 0.600 to 0.709.

### *Controls*

The analyses controlled for several time-invariant characteristics, including *gender* (*boy* or *girl*), *educational level* (*pre-vocational*, *intermediate*, or *pre-university)*, and *immigrant background* (*immigrant* or *non-immigrant*). Educational level was determined based on the respondents' most recent reported level of education. Immigrant background was established based on the country of origin of the respondents' parent(s), whereby response options were *Netherlands*, *Suriname*, *Netherlands Antilles*, *Morocco*, *Turkey*, and *other country*. These countries were selected because a large share of the immigrant population in the Netherlands come from these countries due to colonial past with and a history of labor migration to the Netherlands. Adolescents with at least one parent from a different country than the Netherlands were defined as adolescents with an immigrant background.



## Analytic Approach

### *Identifying Trajectories*

We adopted Latent Class Growth Analysis (LCGA) using Mplus 8.6 (L. K. Muthén & Muthén, 2017b). LCGA explores heterogeneity of growth trajectories within a population by classifying individuals into subgroups based on their response patterns (Jung & Wickrama, 2008). It tests several class solutions, whereby each class represents a growth trajectory indicated by an intercept, slope, and quadratic term estimated from multiple repeated measures. Respectively, these three growth parameters denote the average level of problematic SMU at T1, the average change over time, and whether there is non-linear change. In LCGA-models, the variances and covariances of the growth parameters are constrained to zero, which imposes that individuals within a class have similar growth trajectories.

The problematic SMU sum-score follows a Poisson distribution (Figure 7.1), which does not allow for ordinary LCGA (Reinecke, 2006a). Therefore, we compared the model fit of Poisson and zero-inflated Poisson growth models. We present our findings using the more parsimonious Poisson models, because zero-inflation parameters were not significant and from three classes onwards model fits were comparable (Appendix, Figure A7.1). The trajectories of problematic SMU were estimated in parallel with trajectories of SMU frequency. These co-trajectories were estimated without any covariates, which facilitates interpretation (Van de Schoot et al., 2017). The model specifications are available in the Appendix (Figure A7.2).

The number of classes was established based on the model fit and classification accuracy (Van de Schoot et al., 2017). Model fit was evaluated based on the Bayesian Information Criterion (BIC). We used the Lo-Mendell-Rubin adjusted Likelihood Ratio Test (LMR-LRT) and Bootstrap Likelihood Ratio Test (BLRT) to indicate whether a class solution improved model fit compared to a class solution with one class less ($p < 0.050$). Classification accuracy was evaluated based on the average class membership probability of each class, with values close to 1 indicating good classification. Also, Entropy with values of 0.700 or higher were considered as adequate (Reinecke, 2006a). As typical for latent class analysis, the model selection was based on a trade-off between all of the above-mentioned criteria (Jung & Wickrama, 2008).

The percentage of missing data on the study variables for this part of the analysis ranged from 6.6% (problematic SMU T2) to 65.8% (SMU frequency T4), which was mostly related to dropout. Little's Chi-square test for missing data was significant ($\chi^2(118) = 262.144$, $p < 0.001$), which means that we cannot assume that data were completely missing at random. Consequently, listwise deletion of cases with one or multiple missing values may bias results (Enders & Bandalos, 2001). However, in our analysis, we aimed to limit the bias that is associated with missing data by conducting the LCGA using full information maximum likelihood with robust standard errors (MLR), which retains all 1,419 respondents.

### *Predictors of Trajectories*

Based on the latent class solution from the LCGA, we created a nominal class variable that denotes the most likely class membership for each respondent.

In addition, we computed respondents' average level of subjective wellbeing, self-control, and social competencies using their responses from T1 until T4. These person-specific means denote the time-invariant (i.e., trait-like, stable) part of adolescents' level of subjective wellbeing, self-control, and social competencies. Subsequently, we conducted multivariate multinomial regression analysis to predict class membership with the subjective wellbeing, self-control, and social competencies person-specific means, while controlling for demographic characteristics. In doing so, we specified the measurement error of the class variable using the logits for the classification probabilities for the most likely latent class membership as obtained from the LCGA. This model specification takes into account the uncertainty that is associated with the classification, which improves the accuracy of the multinomial regression estimates (Asparouhov & Muthén, 2014).

There was one missing observation for immigrant background. For the predictors, the percentage of missing data ranged between 6.6% (attention deficit T2) and 65.9% (life satisfaction T4), which was mostly related to dropout. Gender, educational level, and the class variable were complete. The missing data were not found to be completely missing at random ($\chi^2(604) = 802.317$, $p < 0.001$), which means that retaining all respondents is required to limit possible bias (Enders & Bandalos, 2001). However, with the present multinomial model, MLR-estimation did not retain all respondents. Therefore, for the multinomial analysis, we imputed missing values using multiple imputation with chained equations (Royston & White, 2011). In this procedure, missing values were estimated based on predictive mean matching with 'five nearest neighbors', whereby missing values were imputed based on the observed data on the study variables. Imputations were computed in Stata 13.0 (StataCorp, 2013) and exported to Mplus 8.6 (L. K. Muthén & Muthén, 2017b) to conduct the multinomial analysis.



## Preregistration

The subsample selection and analytical approaches were preregistered. In order to improve the analytical approach, we deviated from the preregistration by defining the predictors of the trajectories using the person-specific averages across all waves instead of using only the T1 data. Also, the analysis sample yielded 1,419 adolescents instead of the preregistered 1,414, which was due to a correction on the sample selection. For the remainder, all analyses followed the preregistered procedures. The preregistration and codes for data selection and all analyses may be consulted via https://osf.io/r9t4a/.

# Results

## Descriptive Statistics

Table 7.1 shows the descriptive statistics for all study variables. It shows that the observed average level of problematic SMU was low, whereas the level of SMU frequency was around the midpoint of its scale. Observed averages in life satisfaction, self-esteem, and social competencies were high, whereas attention deficit and impulsivity were low, given the ranges of the respective scales.

## Identifying Trajectories

### *Average Trajectory*

Figure 7.2 shows the estimated average trajectory of problematic SMU and SMU frequency over time. At T1, the average reported level of problematic SMU was 1.153. The course of problematic SMU was non-linear, whereby adolescents' level of problematic SMU first increased, but decreased after T2 ($B_{linear}$ = 0.142, $p$ = 0.015; $B_{quadratic}$ = -0.060, $p$ = 0.002). Also, there was a non-linear trend of SMU frequency, whereby SMU frequency increased until T3, but decreased thereafter ($B_{linear}$ = 0.366, $p < 0.001$; $B_{quadratic}$ = -0.087, $p <$ 0.001).

### *Model Selection*

Table 7.2 shows the fit indices and classification accuracy of six LCGA models. The higher the number of classes, the better the model fit in terms of the BIC and BLRT, as the BIC decreased until the final model and the BLRT *p*-value indicated that adding classes improved model fit compared to a model with one class less ($p < 0.001$). However, for the 5- and 6-class models, the decrease in BIC was relatively small, and for the 6-class model, the LMR-LRT *p*-value

**Table 7.1**

*Descriptive Statistics and Correlations of the Study Variables ($n$ = 1,419)*

| | | $T$ | $M$ / % | $SD$ | Min. | Max. | 1 $r$ | 2 $r$ | 3 $r$ | 4 $r$ | 5 $r$ | 6 $r$ | 7 $r$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Problematic SMU | 1 | 1.129 | 1.494 | 0 | 8 | | | | | | | |
| | | 2 | 1.293 | 1.616 | 0 | 9 | | | | | | | |
| | | 3 | 1.152 | 1.464 | 0 | 9 | | | | | | | |
| | | 4 | 1.065 | 1.431 | 0 | 9 | | | | | | | |
| 2 | SMU frequency | 1 | 3.923 | 1.586 | 1.000 | 7.000 | 0.341*** | | | | | | |
| | | 2 | 4.271 | 1.565 | 1.000 | 7.000 | 0.317*** | | | | | | |
| | | 3 | 4.285 | 1.485 | 1.000 | 7.000 | 0.243*** | | | | | | |
| | | 4 | 4.296 | 1.376 | 1.000 | 7.000 | 0.251*** | | | | | | |
| 3 | Life satisfaction | 1 | 4.932 | 0.757 | 1.143 | 6.000 | -0.282*** | -0.098** | | | | | |
| | | 2 | 4.687 | 0.874 | 1.000 | 6.000 | -0.310*** | -0.089** | | | | | |
| | | 3 | 4.540 | 0.876 | 1.000 | 6.000 | -0.306*** | -0.044 | | | | | |
| | | 4 | 4.476 | 0.884 | 1.000 | 6.000 | -0.241*** | -0.028 | | | | | |
| 4 | Self-esteem | 1 | 3.946 | 0.685 | 1.200 | 5.000 | -0.198*** | -0.066 | 0.516*** | | | | |
| | | 2 | 3.865 | 0.758 | 1.000 | 5.000 | -0.270*** | -0.109*** | 0.628*** | | | | |
| | | 3 | 3.757 | 0.738 | 1.000 | 5.000 | -0.297*** | -0.052 | 0.628*** | | | | |
| | | 4 | 3.730 | 0.745 | 1.000 | 5.000 | -0.180*** | -0.032 | 0.593*** | | | | |
| 5 | Attention deficits | 1 | 2.115 | 0.703 | 1.000 | 4.333 | 0.349*** | 0.193*** | -0.318*** | -0.191*** | | | |
| | | 2 | 2.266 | 0.773 | 1.000 | 5.000 | 0.379*** | 0.236*** | -0.287*** | -0.246*** | | | |
| | | 3 | 2.399 | 0.754 | 1.000 | 5.000 | 0.312*** | 0.150*** | -0.257*** | -0.254*** | | | |
| | | 4 | 2.463 | 0.783 | 1.000 | 5.000 | 0.267*** | 0.108** | -0.199*** | -0.214*** | | | |
| 6 | Impulsivity | 1 | 1.863 | 0.682 | 1.000 | 4.667 | 0.357*** | 0.276*** | -0.170*** | -0.081** | 0.656*** | | |
| | | 2 | 1.926 | 0.745 | 1.000 | 5.000 | 0.357*** | 0.264*** | -0.201*** | -0.167*** | 0.683*** | | |
| | | 3 | 1.947 | 0.678 | 1.000 | 5.000 | 0.308*** | 0.200*** | -0.178*** | -0.168*** | 0.624*** | | |
| | | 4 | 1.934 | 0.650 | 1.000 | 4.000 | 0.241*** | 0.172*** | -0.085* | -0.134*** | 0.642*** | | |
| 7 | Social competence | 1 | 4.401 | 0.628 | 1.800 | 5.000 | -0.197*** | 0.067 | 0.285*** | 0.291*** | -0.156*** | -0.146*** | |
| | | 2 | 4.354 | 0.681 | 1.200 | 5.000 | -0.108*** | 0.117*** | 0.208*** | 0.253*** | -0.148*** | -0.166*** | |
| | | 3 | 4.322 | 0.700 | 1.000 | 5.000 | -0.127*** | 0.098** | 0.303*** | 0.360*** | -0.185*** | -0.214*** | |
| | | 4 | 4.352 | 0.675 | 1.200 | 5.000 | -0.137** | 0.211*** | 0.275*** | 0.308*** | -0.115** | -0.060 | |

*Notes.* $T$ = timepoint (i.e., wave); SMU = social media use; $M$ = mean; Prop. = proportion; $SD$ = standard deviation; Min. = minimum; Max. = maximum; $r$ = pairwise correlation. Means and standard deviations are based on complete data.

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

**Table 7.1 (Continued)**

*Descriptive Statistics and Correlations of the Study Variables ($n$ = 1,419)*

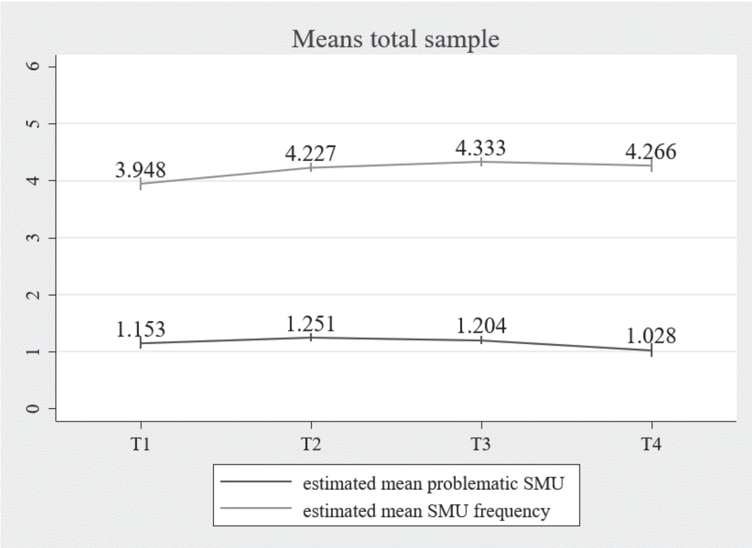
| | | $T$ | $M$ / % | $SD$ | Min. | Max. | 1<br>$r$ | 2<br>$r$ | 3<br>$r$ | 4<br>$r$ | 5<br>$r$ | 6<br>$r$ | 7<br>$r$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 8 | Female | 1-4 | 45.9 | | 0 | 1 | -0.060 | 0.163*** | -0.102* | -0.169*** | -0.150** | -0.265*** | 0.161** |
| | | | | | | | 0.079* | 0.276*** | -0.112** | -0.148*** | -0.022 | -0.164*** | 0.231*** |
| | | | | | | | 0.084* | 0.213*** | -0.032 | -0.088* | -0.073 | -0.177*** | 0.208*** |
| | | | | | | | 0.066 | 0.196*** | -0.053 | -0.047 | -0.068 | -0.117* | 0.283*** |
| 9 | Pre-vocational education | 1-4 | 57.8 | | 0 | 1 | 0.322*** | 0.237*** | -0.082 | -0.015 | 0.135** | 0.221*** | -0.097 |
| | | | | | | | 0.150*** | 0.171*** | 0.010 | -0.064 | 0.052 | 0.190*** | -0.035 |
| | | | | | | | 0.104** | 0.164*** | 0.012 | -0.010 | -0.026 | 0.076* | -0.035 |
| | | | | | | | 0.094* | 0.099** | -0.011 | -0.096* | -0.117** | -0.011 | -0.103** |
| 10 | Immigrant background | 1-4 | 21.8 | | 0 | 1 | 0.076 | 0.046 | -0.022 | -0.043 | -0.077 | -0.005 | 0.028 |
| | | | | | | | 0.041 | -0.024 | 0.102* | 0.099** | -0.106** | -0.015 | 0.002 |
| | | | | | | | 0.017 | -0.034 | <0.001 | 0.075 | -0.066 | 0.048 | -0.075 |
| | | | | | | | -0.019 | -0.087 | -0.159* | <0.001 | -0.040 | -0.064 | -0.252*** |

*Notes.* $T$ = timepoint (i.e., wave); SMU = social media use; $M$ = mean; $SD$ = standard deviation; Min. = minimum; Max. = maximum; $r$ = pairwise correlation. Means and standard deviations are based on complete data.

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

**Figure 7.2**

*Average Co-Trajectory of Problematic SMU and SMU Frequency, n = 1,419*




*Notes.* Data labels show the model estimated means based on the one-class solution. Vertical bars denote the 95% confidence intervals.



was not significant (*p* = 0.172). Furthermore, the Entropy of the 5- and 6-class models was below 0.700, which suggests inaccurate classification accuracy. Hence, the 1- to 4-class solutions seemed more eligible. From these models, we selected and further interpreted the 4-class solution, because this model showed the best model fit according to all fit indices, and the Entropy was appropriate (0.719).

**Table 7.2**

*Model Fit Indices and Classification Accuracy LCGA models (n = 1,419)*

| Par. | C | BIC | Entropy | LMR-LRT value | LMR-LRT *p*-value | BLRT *p*-value | Min. class size | Max. class size | Min. probability | Max. probability |
|---|---|---|---|---|---|---|---|---|---|---|
| 10 | 1 | 25439.225 | | | | | 1,419 | 1,419 | 1 | 1 |
| 17 | 2 | 23588.660 | 0.723 | 1864.667 | <0.001 | <0.001 | 691 | 728 | 0.916 | 0.918 |
| 24 | 3 | 23081.855 | 0.708 | 546.846 | <0.001 | <0.001 | 387 | 578 | 0.847 | 0.891 |
| 31 | 4 | 22868.471 | 0.719 | 259.088 | <0.001 | <0.001 | 224 | 527 | 0.728 | 0.896 |
| 38 | 5 | 22806.901 | 0.673 | 110.204 | 0.035 | <0.001 | 238 | 350 | 0.748 | 0.874 |
| 45 | 6 | 22780.090 | 0.665 | 76.115 | 0.172 | <0.001 | 139 | 348 | 0.650 | 0.802 |

*Notes.* LCGA = Latent Class Growth Analysis; Par. = number of free parameters; C = number of classes; BIC = Bayesian Information Criterion, LMR-LRT = Lo-Mendell-Rubin Likelihood Ratio Test; BLRT = Bootstrap Likelihood Ratio Test; Min. = minimum; Max. = maximum.

### *Interpretation of Trajectories*

Table 7.3 reports the model estimates and group sizes of the classes from the 4-class solution and Figure 7.3 shows the estimated means of problematic SMU and SMU frequency. In the first class, adolescents reported relatively high levels of problematic SMU ($M_{T1}$ = 2.430). Their level of problematic SMU followed a non-linear trend, whereby problematic SMU first increased, but decreased after T2. Adolescents in Class 1 also reported higher levels of SMU frequency than adolescents in the other classes ($M_{T1}$ = 5.264). The course of their SMU frequency was non-linear, whereby they first showed an increase, followed by a decrease. In Class 2, which had the least members (15.8%), the average level of problematic SMU was also relatively high, but stable over time ($M_{T1}$ = 1.973). Adolescents within this group, however, reported average levels of SMU frequency and this level remained stable over time ($M_{T1}$ = 3.628). In Class 3, adolescents reported the lowest level of problematic SMU, which was stable over time ($M_{T1}$ = 0.233). Also, adolescents' SMU frequency was lower than average, with no significant changes over time ($M_{T1}$ = 2.249). In Class 4, which included the most members (37.1%), adolescents' level of problematic SMU was also lower than average and stable over time ($M_{T1}$ = 0.515), but the level of SMU frequency over time was higher than in Class 2 and 3, with a significant non-linear course: SMU frequency increased, but this increase became smaller over time and eventually decreased in T4 ($M_{T1}$ = 4.186).

**Table 7.3**

*Model Estimates 4-class Solution*

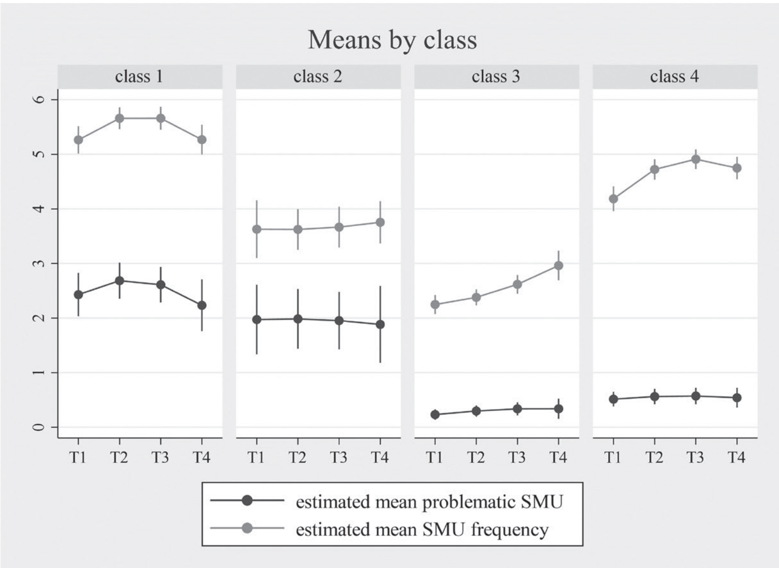
| | **Class 1: *n* = 350 (24.7%) Variably high problematic SMU, variably high SMU frequency** | | | **Class 2: *n* = 224 (15.8%) Persistently high problematic SMU, persistently average SMU frequency** | | | **Class 3: *n* = 318 (22.4%) Persistently low problematic SMU, persistently low SMU frequency** | | | **Class 4: *n* = 527 (37.1%) Persistently low problematic SMU, variably high SMU frequency** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | ***B*** | ***SE*** | **D.** | ***B*** | ***SE*** | **D.** | ***B*** | ***SE*** | **D.** | ***B*** | ***SE*** | **D.** |
| **Problematic SMU** | | | | | | | | | | | | |
| Intercept | 0.888*** | 0.084 | a | 0.680*** | 0.165 | a | -1.458*** | 0.212 | b | -0.665*** | 0.131 | c |
| Slope | 0.164 | 0.089 | a | 0.017 | 0.150 | a | 0.310 | 0.256 | a | 0.128 | 0.182 | a |
| Quadratic | -0.064* | 0.031 | a | -0.011 | 0.053 | a | -0.062 | 0.088 | a | -0.037 | 0.060 | a |
| **SMU frequency** | | | | | | | | | | | | |
| Intercept | 5.264*** | 0.128 | a | 3.628*** | 0.269 | b | 2.249*** | 0.089 | c | 4.186*** | 0.116 | b |
| Slope | 0.592*** | 0.137 | ac | -0.027 | 0.294 | ab | 0.077 | 0.106 | b | 0.711*** | 0.119 | c |
| Quadratic | -0.197*** | 0.042 | a | 0.023 | 0.083 | b | 0.054 | 0.037 | b | -0.174*** | 0.036 | a |

*Notes.* SMU = social media use; *B* = unstandardized coefficient; *SE* = standard error; D. = difference, columns with different letters denote that estimates differed significantly across the respective classes as obtained by *z*-scores of the parameter differences.
*** *p* < 0.001, *p* ** < 0.01, * *p* < 0.05;

To gain a more detailed understanding of the classes, we report on some of the class comparisons using the *z*-scores of the parameter differences (Table 7.3). The intercept of problematic SMU differed significantly between all classes, except between Classes 1 and 2. This means that except for these two classes, all classes had different levels of problematic SMU at T1. The intercept of SMU frequency differed across all classes, except for Classes 2 and 4. Also, the non-linear trends of SMU frequency in Classes 1 and 4 were not significantly different.

**Figure 7.3**

*Average Co-Trajectory of Problematic SMU and SMU Frequency by Latent Class, n = 1,419*




*Note*. Vertical bars denote the 95% confidence intervals.

## Predictors of Trajectories

Table 7.4 displays the differences in adolescents' demographic characteristics, subjective wellbeing, self-control, and social competencies by class. We examined whether these factors predicted class membership using multivariate multinomial regression. Given that Class 4 had the most members, we conducted the multinomial analysis using Class 4 as the reference group. Hence, estimates from this analysis indicate the extent to which, for example, higher levels of attention deficits, increase the probability of following the trajectories of Classes 1, 2, or 3, relative to Class 4. For reference, additional findings from stepwise analyses can be consulted in the Appendix (Tables A7.2-A7.4).

**Table 7.4**

*Observed Means and Proportions Study Variables, by Class (n = 1,419)*

| | **Pooled sample** | | **Class 1: Variably high problematic SMU, variably high SMU frequency** | | **Class 2: Persistently high problematic SMU, persistently average SMU frequency** | | **Class 3: Persistently low problematic SMU, persistently low SMU frequency** | | **Class 4: Persistently low problematic SMU, variably high SMU frequency** | |
|---|---|---|---|---|---|---|---|---|---|---|
| | ***M/%*** | ***SD*** | ***M/%*** | ***SD*** | ***M/%*** | ***SD*** | ***M/%*** | ***SD*** | ***M/%*** | ***SD*** |
| **Controls** | | | | | | | | | | |
| Girl | 45.9% | | 58.0% | | 35.7% | | 30.8% | | 51.4% | |
| Pre-vocational education | 57.8% | | 70.0% | | 59.8% | | 50.3% | | 53.3% | |
| Intermediate education | 28.5% | | 22.0% | | 30.4% | | 29.9% | | 31.3% | |
| Pre-university education | 13.7% | | 8.0% | | 9.8% | | 19.8% | | 15.4% | |
| Immigrant background[1] | 21.8% | | 21.4% | | 26.8% | | 22.6% | | 19.5% | |
| | | | | | | | | | | |
| **Subjective wellbeing** | | | | | | | | | | |
| Life satisfaction[1] | 4.661 | 0.595 | 4.449 | 0.644 | 4.500 | 0.616 | 4.786 | 0.558 | 4.796 | 0.512 |
| Self-esteem[1] | 3.815 | 0.491 | 3.701 | 0.503 | 3.668 | 0.489 | 3.944 | 0.474 | 3.877 | 0.462 |
| | | | | | | | | | | |
| **Self-control** | | | | | | | | | | |
| Attention deficit[1] | 2.285 | 0.526 | 2.555 | 0.507 | 2.383 | 0.490 | 2.081 | 0.501 | 2.188 | 0.485 |
| Impulsivity[1] | 1.918 | 0.484 | 2.204 | 0.513 | 1.989 | 0.447 | 1.676 | 0.388 | 1.843 | 0.428 |
| | | | | | | | | | | |
| **Social competencies** | | | | | | | | | | |
| Perceived friendship competence[1] | 4.321 | 0.460 | 4.324 | 0.430 | 4.035 | 0.510 | 4.297 | 0.477 | 4.454 | 0.383 |

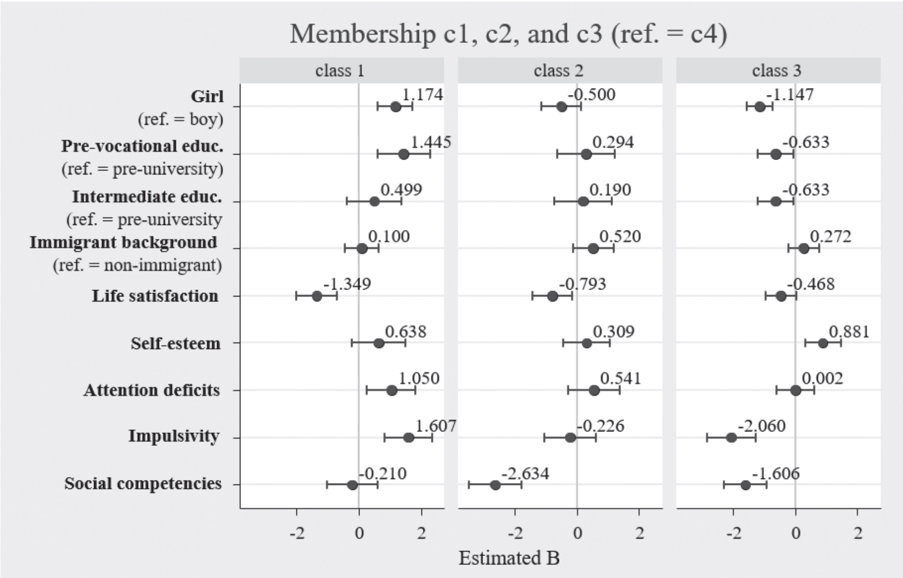
*Notes.* SMU = social media use; *M* = mean*; SD* = standard deviation.
[1] Proportion, means, and standard deviations for the pooled sample slightly differ from those reported in the sample description and Table 7.1. This is because the present table presents the proportions, means, and standard deviations based on the imputed data, whereas Table 7.1 presents the proportions, means and standard deviations based on the complete data.

### *Class 1: Variably High Problematic SMU, Variably High SMU Frequency*

Figure 7.4 shows that compared to Class 4, girls and pre-vocational educated adolescents were more likely to be in Class 1 than boys and pre-university adolescents, respectively ($B$ = 1.174, $p$ < 0.001, OR = 3.241 and $B$ = 1.445, $p$ = 0.001, OR = 4.250). Lower life satisfaction ($B$ = -1.349, $p$ < 0.001, OR = 0.263), higher attention deficit ($B$ = 1.050, $p$ = 0.008, OR = 2.914), and higher impulsivity ($B$ = 1.607, $p$ < 0.001, OR = 5.051), were associated with a greater probability of being in Class 1 compared to Class 4.

**Figure 7.4**

*Estimates From Multivariate Multinomial Regression Analysis on Class Membership, n = 1,419*




*Notes.* Estimates are logit coefficients. Ref. = reference category. Class 1 = variably high problematic SMU, variably high SMU frequency; Class 2 = persistently high problematic SMU, persistently average SMU frequency; Class 3 = persistently low problematic SMU, persistently low SMU frequency; Class 4 = persistently low problematic SMU, variably high SMU frequency.

### *Class 2: Persistently High Problematic SMU, Persistently Average SMU Frequency*

Class 2 and 4 did not vary by demographic characteristics. The lower the level of life satisfaction and social competencies, the higher the probability of being in Class 2 compared to Class 4 ($B$ = -0.793, $p$ = 0.013, OR = 0.454; $B$ = -2.634, $p$ < 0.001, OR = 0.073).

***Class 3: Persistently Low Problematic SMU, Persistently Low SMU Frequency***

Relative to Class 4, boys were more likely to be in Class 3 than girls ($B$ = -1.147 $p$ < 0.001, OR = 0.318). Also, adolescents attending pre-university education had a higher probability of being in Class 3 than adolescents attending intermediate or pre-vocational education ($B$ = -0.633, $p$ = 0.028, OR = 0.532; $B$ = -0.633, $p$ = 0.031, OR = 0.531). Higher self-esteem ($B$ = 0.881, $p$ = 0.003, OR = 2.423), lower impulsivity ($B$ = -2.060, $p$ < 0.001, OR = 0.130), and poorer social competencies ($B$ = -1.606, $p$ < 0.001, OR = 0.202) were associated with a greater probability of being in Class 3.

***Additional Class Comparisons***

We also explored other class differences by repeating the multivariate multinomial analysis with other reference categories (see Appendix, Table A7.5). This analysis was not preregistered and therefore considered as additional exploratory analysis. Comparing the classes with the highest level of problematic SMU (Classes 1 and 2), results showed that levels of impulsivity and social competence were higher in Class 1 than in Class 2 ($B$ = 1.833, $p$ < 0.001, OR = 6.327; $B$ = 2.424, $p$ < 0.001, OR = 11.536). In addition, adolescents in Class 1 showed lower life satisfaction ($B$ = -0.881, $p$ = 0.020, OR = 0.423), higher attention deficit and impulsivity ($B$ = 1.048, $p$ = 0.017, OR = 2.928; $B$ = 3.667, $p$ < 0.001, OR = 41.106), and stronger social competencies ($B$ = 1.369, $p$ = 0.005, OR = 4.182), than adolescents in Class 3. Adolescents in Class 2 showed higher impulsivity and weaker social competencies than adolescents in Class 3 ($B$ = 1.834, $p$ < 0.001, OR = 6.392; $B$ = -1.028, $p$ = 0.014, OR = 0.365).

# Discussion

The present study investigated adolescents' trajectories of problematic SMU in parallel with their trajectories of SMU frequency in early and middle adolescence. Four subgroups were identified: two subgroups that showed relatively high levels of problematic SMU over time, of which one reported high and one reported average levels of SMU frequency, and two subgroups that showed low levels of problematic SMU over time, of which one reported low and one reported high levels of SMU frequency. In the subgroup with relatively high levels of problematic SMU and SMU frequency, problematic

SMU first increased, but decreased after the second year, although the level of problematic SMU remained high. In the other three subgroups, the levels of problematic SMU were persistent over time. The subgroup with low levels of problematic SMU but high SMU frequency had the most members. Relative to this group, adolescents in the two subgroups with high levels of problematic SMU showed the most problematic profiles regarding their psychosocial characteristics, although the profiles of these two subgroups differed. Particularly, although both subgroups showed lower levels of subjective wellbeing (i.e., lower life satisfaction), the subgroup with high levels of problematic SMU and SMU frequency showed lower levels of self-control (i.e., higher attention deficit and impulsivity), whereas the subgroup with high levels of problematic SMU and average SMU frequency reported poorer social competencies (i.e., perceived friendship competencies).

In line with studies investigating developmental trajectories of mental health problems and deviant behaviors throughout adolescence, such as depressive symptoms, aggression, delinquency, or binge drinking (Bongers et al., 2004; Chassin et al., 2002; Dekker et al., 2007; Reinecke, 2006a), problematic SMU evolved through persistently high, persistently low, and variable trajectories. For both subgroups with relatively high levels of problematic SMU, the level of problematic SMU remained high throughout the entire four-year period, implying that high levels of problematic SMU are rather persistent over time. This finding is plausible, given the addiction-like nature of problematic SMU. Characteristic for behavioral addiction is that it is difficult to resist the temptation to engage in the behavior or to reduce it, and that it persists over a significant period of time (Kardefelt-Winther et al., 2017). Also, it is conceivably challenging for adolescents with higher levels of problematic SMU to regain control over their SMU, given that they can access social media on their smartphones anytime wherever they are. Furthermore, nowadays, abstaining from social media may be difficult for young adolescents, given that many activities that are relevant to their social and educational development take place online. For example, abstaining may come at the expense of social connection with peers or schoolwork. These functions of social media may make it almost impossible to resist the temptation and impulse to use social media, and thus to overcome problematic SMU.

Notwithstanding the finding that higher levels of problematic SMU remained high, there may still be adolescents with more variable trajectories of problematic SMU. After all, the present study investigated *average* subgroup trajectories, whereas there may be individual differences in trajectories and their development. Furthermore, the course of adolescents' problematic SMU may change when they enter late adolescence, which was not measured by the present study. For example, research shows that for some subgroups of adolescents, problem behaviors, such as depressive symptoms and binge drinking, may increase or decrease during late adolescence (Chassin et al., 2002; Dekker et al., 2007).

Although there were two groups with relatively high levels of problematic SMU compared to the average level in the sample and reported in other research (Boer, Stevens, Finkenauer, Koning, et al., 2021), the absolute levels of problematic SMU within these two groups were rather moderate. Nevertheless, moderate levels of problematic SMU may already threaten important life domains, as cross-level research shows that endorsing moderate levels of problematic SMU is associated with a high risk of, for example, reporting schoolwork pressure and poor sleep quality (Boer, Stevens, Finkenauer, Koning, et al., 2021). However, longitudinal research is required to establish whether moderate levels of problematic problems indeed increase such problems over time. This research is considered important, because if moderate levels of problematic SMU are harmful to young adolescents, then this highlights the importance of prevention and intervention programs at schools aimed at decreasing adolescents' (risk of developing) problematic SMU. After all, our findings suggest that a substantial group of young adolescents experience such levels of problematic SMU for a prolonged period of time.

Another important finding was that the four identified subgroups showed different co-developments of problematic SMU and SMU frequency. For example, in the largest subgroup, adolescents reported persistently low levels of problematic SMU with variably high levels of SMU frequency. Another subgroup, though relatively small, showed high levels of problematic SMU with average SMU frequency, which suggests that some adolescents endorse problematic SMU without using social media intensively. Overall, the finding that trajectories of SMU frequency do not necessarily parallel trajectories of problematic SMU supports the proposition that problematic SMU and SMU frequency should be considered as different dimensions related to SMU (Boer, Van den Eijnden, et al., 2020). This finding is in line with large-scale and case studies on gaming, which show that excessive gaming does not necessarily imply problematic gaming (Griffiths, 2010; Király, Tóth, et al., 2017). Furthermore, the finding that the subgroup with persistently low levels of problematic SMU and variably high SMU frequency had the most members informs parents, teachers, and policymakers who are concerned about adolescents' SMU that it is rather normative that adolescents display high SMU frequency and that this does not necessarily imply experiencing problematic SMU. Thus, rather than problematizing high SMU frequency, it is important to recognize that it is often common behavior for today's adolescents instead of a risk factor for problematic SMU.

The two subgroups with relatively high levels of problematic SMU showed different profiles. In one subgroup, adolescents reported high levels of SMU frequency, were more often female, more often followed pre-vocational education, and reported low subjective wellbeing and self-control, which is in line with previously found predictors of problematic SMU (Bányai et al., 2017; Mérelle et al., 2017). The profile of the other subgroup was less typical, because adolescents in this group showed average levels of SMU frequency. This latter group also showed lower subjective wellbeing, but in addition, reported poorer social competencies. One possible explanation for the finding that adolescents with poor social competencies and high levels of problematic SMU reported average SMU frequency may be a mismatch between their desired and actual social network size. Due to their lack of social competencies, they may not have the social network they desire. Consequently, they may become preoccupied with the social media activities of others, without having the desired social network to actively interact with online. Overall, these findings confirm that psychosocial vulnerabilities, including poor subjective wellbeing, low self-control, and low social competence, are linked to problematic SMU (Caplan, 2003; Davis, 2001; Mérelle et al., 2017), but they also extend the literature in two ways. First, these characteristics increase the risk of experiencing *persistently* higher levels of problematic SMU during early and middle adolescence, which implies that vulnerable adolescents face prolonged sensitivity to problematic SMU throughout this period. Second, problematic SMU manifests in different ways, depending on the risk profile: While problematic SMU of adolescents with low self-control seems externally visible through high SMU frequency, problematic SMU of adolescents with low social competencies may be more internally present, given that they do not show high SMU frequency. This finding suggests that for this latter group, problematic SMU may be more difficult to detect for professionals and parents that are concerned with the wellbeing of young adolescents.

In addition, we did not observe a variable trajectory that captured the onset of problematic SMU, which implies that problematic SMU may emerge more at the start of early adolescence. Correspondingly, research shows that 11-year-olds may already endorse multiple problematic SMU criteria (Stevens et al., 2018). Other research among Dutch children shows that in 2017, the percentage of 10-year-olds that used Whatsapp, Snapchat, and Instagram was 69%, 25%, and 19%, respectively. Among 11-year-olds, this was 82%, 30%, and 35%, respectively (Kennisnet, 2017). Given that the majority of the 10- and 11-year-olds use social media and that they may already experience problematic SMU in this period, it is important that parents and teachers monitor and support children around this age who experience severe problems in regulating their use or whose use goes at the expense of activities important to children's health.

This study showed that lower subjective wellbeing and self-control predicted problematic SMU, although this was not found in previous research using the same data (Boer, Stevens, et al., 2020; Boer, Stevens, Finkenauer, De Looze, et al., 2021). It should be noted, however, that previous research focused on within-person processes and showed that adolescents with lower levels of subjective wellbeing or self-control *relative to their individual average* did not show an *increase in problematic SMU*. The present study focused on between-person comparisons and showed that adolescents with lower levels of subjective wellbeing and self-control *relative to other adolescents* were likely to report *persistent and variable high levels of problematic SMU*. Together, this suggests that particularly the between-person (i.e., trait-like) differences in wellbeing and self-control may determine adolescents' vulnerability to problematic SMU.

## Limitations and Future Directions

Findings of the present study should be interpreted in light of several limitations. First, we investigated adolescents' trajectories during a limited time span, that is, four years within early and middle adolescence. During this period, social media may play a larger role in adolescents' daily lives than in other periods, because this period typically revolves around forming new friendships, exploring new perspectives, and constructing and sharing personal narratives, which can be facilitated by social media. When these developmental tasks are (partly) fulfilled and personal needs change, different trajectories may emerge. As such, we expect that findings from the present study cannot be generalized to older adolescents. Future research comparing trajectories of problematic SMU across younger and older adolescents would improve our understanding of adolescents' problematic SMU in the context of their developmental period. Second, the present study only assessed trajectories of Dutch adolescents. There are substantial cross-national differences in young adolescents' level of problematic SMU and within the European region, high levels of problematic SMU are the least prevalent in the Netherlands (Boer, Van den Eijnden, et al., 2020). As such, trajectories of Dutch adolescents may deviate from trajectories of adolescents from other cultures. Third, we used self-report measures to indicate SMU frequency, which may have limited accuracy (Junco, 2013). Researchers stressed that the frequency of SMU may be difficult to recall and to estimate (Parry et al., 2020), which is plausible given that SMU typically occurs fragmented throughout the entire day. More objective assessments would be necessary to diminish the influence of recall biases, which furthermore also reduce socially desirable responding biases. Hence, to gain more insight into the co-trajectory of adolescents' SMU frequency and problematic SMU, replicating our study using more objective measures of SMU, such as time tracking applications, are considered promising. Fourth, we determined the time-invariant (i.e., trait-like, stable) part of adolescents' level of subjective wellbeing, self-control, and social competencies based on four waves of data across four years. However, a longer time frame may facilitate more accurate estimates of trait-like psychosocial factors. Therefore, to gain more robust insights into the explanatory role of the investigated psychosocial characteristics in adolescents' trajectories of problematic SMU, more research using longitudinal data across a longer time span (e.g., from middle childhood to late adolescence) is considered important. Fifth, because participating schools were not sampled through a random sampling selection procedure, the generalizability of our findings to the young adolescent population may be limited. Sixth, the present study dealt with considerable amounts of missing data. Although we aimed to limit any potential bias related to missing data by applying modern missing data techniques including full information maximum likelihood and multiple imputation instead of, for example, listwise deletion (Enders & Bandalos, 2001; Peeters et al., 2015), we acknowledge that we cannot exclude the possibility that the missing data affected the estimates of the present analyses. Considering the fifth and sixth limitation, prospective longitudinal studies on trajectories of problematic SMU using more representative and complete samples are warranted. Seventh, the present study measured one particular social competence, namely perceived friendship competencies. Future studies on other social competencies in relation with trajectories of problematic SMU may enhance current knowledge on the role of young adolescents' social competencies in developing problematic SMU. In doing so, focusing on peer reputation is considered promising, given that young adolescents often perceive this as highly important (LaFontana & Cillessen, 2010).

## Conclusion

Given the increasing evidence suggesting that problematic SMU hampers young adolescents' wellbeing, it is important to identify who develops problematic SMU and how it develops during adolescence. The present study is a first step to identify trajectories of problematic SMU among young adolescents and thereby uniquely contributes towards understanding the course of problematic SMU. We identified two subgroups of adolescents who showed relatively high levels of problematic SMU that remained high over time, which suggests that problematic SMU is likely to persist. Adolescents in these two subgroups showed different profiles: One subgroup was characterized by high SMU frequency over time, low life satisfaction, and low self-control, whereas the other subgroup was characterized by average SMU frequency over time, low life satisfaction, and poorer social competencies. Developing prevention and intervention programs on (reducing levels of) problematic SMU may be important, given the persistent nature of problematic SMU among young adolescents. Such programs may target adolescents' psychosocial vulnerabilities that possibly play a role in developing problematic SMU. Notwithstanding these findings, most adolescents endorsed persistently low levels of problematic SMU with high SMU frequency, suggesting that high SMU frequency is normative and not necessarily a risk factor for developing problematic SMU.

# Appendix

**Table A7.1**

*Difference in Latent Class Growth Model Estimates, by Sample (n = 1,419)*

| | Problematic SMU | | SMU frequency | |
|---|---|---|---|---|
| **Sample 1** | **Estimate** | ***SE*** | **Estimate** | ***SE*** |
| Intercept | -0.204** | 0.067 | 3.992*** | 0.067 |
| Slope | -0.031 | 0.033 | 0.149*** | 0.026 |
| Variance intercept | 0.729*** | 0.068 | 1.421*** | 0.090 |
| Variance slope | 0.029* | 0.015 | 0.013 | 0.015 |
| **Sample 2** | **Estimate** | ***SE*** | **Estimate** | ***SE*** |
| Intercept | -0.093 | 0.061 | 4.081*** | 0.065 |
| Slope | 0.027 | 0.033 | 0.169*** | 0.033 |
| Variance intercept | 0.780*** | 0.071 | 1.378*** | 0.096 |
| Variance slope | 0.014 | 0.022 | 0.014 | 0.023 |
| **Differences between samples 1 and 2** | **Estimate** | ***z*** | **Estimate** | ***z*** |
| Intercept | -0.111 | -1.222 | -0.090 | -0.968 |
| Slope | -0.058 | -1.249 | -0.020 | -0.487 |
| Variance intercept | -0.051 | -0.517 | 0.043 | 0.340 |
| Variance slope | 0.015 | 0.571 | -0.001 | -0.038 |

*Notes*. SMU = social media use; SE = standard error; z = z-score. Sample 1 $n$ = 799 (56.3%), sample 2 $n$ = 620 (43.7%). Estimates for Problematic SMU were based on Poisson regression.
*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

**Table A7.2**

*Results Multinomial Regression, Membership Class 1 (n = 1,419)*

| | Class 1: variably high problematic SMU, variably high SMU frequency (ref. = class 4: persistently low problematic SMU, variably high SMU frequency) | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Model A** | | | **Model B** | | | **Model C** | | | **Model D** | | | **Model E (Figure 7.4)** | | |
| | ***B*** | ***SE*** | ***OR*** | ***B*** | ***SE*** | ***OR*** | ***B*** | ***SE*** | ***OR*** | ***B*** | ***SE*** | ***OR*** | ***B*** | ***SE*** | ***OR*** |
| **Controls** | | | | | | | | | | | | | | | |
| Girl (ref. = boy) | 0.445* | 0.192 | 1.560 | 0.376 | 0.213 | 1.457 | 1.190*** | 0.257 | 3.288 | 0.643** | 0.203 | 1.903 | 1.174*** | 0.289 | 3.241 |
| Pre-vocational education (ref. = pre-university) | 1.319*** | 0.340 | 3.741 | 1.256*** | 0.337 | 3.511 | 1.501** | 0.439 | 4.489 | 1.259*** | 0.350 | 3.523 | 1.445** | 0.433 | 4.250 |
| Intermediate education (ref. = pre-university) | 0.482 | 0.364 | 1.619 | 0.314 | 0.360 | 1.369 | 0.696 | 0.464 | 2.006 | 0.453 | 0.372 | 1.573 | 0.499 | 0.455 | 1.649 |
| Immigrant background (ref. = non-immigrant) | -0.002 | 0.225 | 0.998 | 0.071 | 0.239 | 1.074 | 0.112 | 0.264 | 1.120 | -0.045 | 0.233 | 0.956 | 0.100 | 0.279 | 1.108 |
| **Subjective wellbeing** | | | | | | | | | | | | | | | |
| Life satisfaction | | | | -1.530*** | 0.298 | 0.218 | | | | | | | -1.349*** | 0.331 | 0.263 |
| Self-esteem | | | | 0.098 | 0.331 | 1.115 | | | | | | | 0.638 | 0.441 | 1.940 |
| **Self-control** | | | | | | | | | | | | | | | |
| Attention deficit | | | | | | | 1.341*** | 0.356 | 3.875 | | | | 1.050** | 0.399 | 2.914 |
| Impulsivity | | | | | | | 1.599*** | 0.338 | 4.972 | | | | 1.607*** | 0.393 | 5.051 |
| **Social competencies** | | | | | | | | | | | | | | | |
| Perceived friendship competence | | | | | | | | | | -1.296*** | 0.328 | 0.276 | -0.210 | 0.415 | 0.824 |

*Notes.* SMU = social media use; *B* = logit coefficient; *SE* = standard error; *OR* = Odds ratio.
*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

**Table A7.3**

*Results Multinomial Regression, Membership Class 2 (n = 1,419)*

| | **Class 2: persistently high problematic SMU, persistently average SMU frequency (ref. = class 4: persistently low problematic SMU, variably high SMU frequency)** | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Model A** | | | **Model B** | | | **Model C** | | | **Model D** | | | **Model E (Figure 7.4)** | | |
| | ***B*** | ***SE*** | ***OR*** | ***B*** | ***SE*** | ***OR*** | ***B*** | ***SE*** | ***OR*** | ***B*** | ***SE*** | ***OR*** | ***B*** | ***SE*** | ***OR*** |
| **Controls** | | | | | | | | | | | | | | | |
| Girl (ref. = boy) | -0.916*** | 0.260 | 0.400 | -1.050*** | 0.271 | 0.350 | -0.683* | 0.273 | 0.505 | -0.393 | 0.286 | 0.676 | -0.500 | 0.327 | 0.610 |
| Pre-vocational education (ref. = pre-university) | 0.447 | 0.417 | 1.563 | 0.439 | 0.438 | 1.552 | 0.432 | 0.415 | 1.540 | 0.373 | 0.476 | 1.457 | 0.294 | 0.471 | 1.347 |
| Intermediate education (ref. = pre-university) | 0.388 | 0.424 | 1.474 | 0.327 | 0.447 | 1.387 | 0.296 | 0.431 | 1.345 | 0.419 | 0.488 | 1.524 | 0.190 | 0.474 | 1.210 |
| Immigrant background (ref. = non-immigrant) | 0.608* | 0.272 | 1.837 | 0.682* | 0.287 | 1.979 | 0.701* | 0.287 | 2.017 | 0.473 | 0.323 | 1.611 | 0.520 | 0.333 | 1.691 |
| | | | | | | | | | | | | | | | |
| **Subjective wellbeing** | | | | | | | | | | | | | | | |
| Life satisfaction | | | | -1.124** | 0.327 | 0.327 | | | | | | | -0.793* | 0.321 | 0.454 |
| Self-esteem | | | | -0.646 | 0.350 | 0.526 | | | | | | | 0.309 | 0.386 | 1.372 |
| | | | | | | | | | | | | | | | |
| **Self-control** | | | | | | | | | | | | | | | |
| Attention deficit | | | | | | | 1.082** | 0.354 | 2.981 | | | | 0.541 | 0.429 | 1.752 |
| Impulsivity | | | | | | | 0.264 | 0.367 | 1.308 | | | | -0.226 | 0.424 | 0.805 |
| | | | | | | | | | | | | | | | |
| **Social competencies** | | | | | | | | | | | | | | | |
| Perceived friendship competence | | | | | | | | | | -2.885*** | 0.414 | 0.057 | -2.634*** | 0.430 | 0.073 |

*Notes.* SMU = social media use; *B* = logit coefficient; *SE* = standard error; *OR* = Odds ratio.
*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

**Table A7.4**

*Results Multinomial Regression, Membership Class 3 (n = 1,419)*

| | **Class 3: persistently low problematic SMU, persistently low SMU frequency (ref. = class 4: persistently low problematic SMU, variably high SMU frequency)** | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Model A** | | | **Model B** | | | **Model C** | | | **Model D** | | | **Model E (Figure 7.4)** | | |
| | ***B*** | ***SE*** | ***OR*** | ***B*** | ***SE*** | ***OR*** | ***B*** | ***SE*** | ***OR*** | ***B*** | ***SE*** | ***OR*** | ***B*** | ***SE*** | ***OR*** |
| **Controls** | | | | | | | | | | | | | | | |
| Girl (ref. = boy) | -1.098*** | 0.188 | 0.333 | -1.051*** | 0.196 | 0.350 | -1.360*** | 0.196 | 0.257 | -0.932*** | 0.195 | 0.394 | -1.147*** | 0.212 | 0.318 |
| Pre-vocational education (ref. = pre-university) | -0.581* | 0.242 | 0.560 | -0.580* | 0.245 | 0.560 | -0.571* | 0.254 | 0.565 | -0.633* | 0.255 | 0.531 | -0.633* | 0.288 | 0.532 |
| Intermediate education (ref. = pre-university) | -0.533* | 0.261 | 0.587 | -0.595* | 0.266 | 0.552 | -0.549* | 0.269 | 0.578 | -0.561* | 0.273 | 0.570 | -0.633* | 0.293 | 0.531 |
| Immigrant background (ref. = non-immigrant) | 0.374 | 0.219 | 1.453 | 0.368 | 0.225 | 1.446 | 0.377 | 0.232 | 1.459 | 0.331 | 0.227 | 1.394 | 0.272 | 0.253 | 1.315 |
| **Subjective wellbeing** | | | | | | | | | | | | | | | |
| Life satisfaction | | | | -0.574* | 0.250 | 0.564 | | | | | | | -0.468 | 0.251 | 0.628 |
| Self-esteem | | | | 0.518 | 0.269 | 1.681 | | | | | | | 0.881** | 0.294 | 2.423 |
| **Self-control** | | | | | | | | | | | | | | | |
| Attention deficit | | | | | | | 0.162 | 0.277 | 1.180 | | | | 0.002 | 0.307 | 1.006 |
| Impulsivity | | | | | | | -1.776*** | 0.386 | 0.172 | | | | -2.060*** | 0.406 | 0.130 |
| **Social competencies** | | | | | | | | | | | | | | | |
| Perceived friendship competence | | | | | | | | | | -1.170*** | 0.289 | 0.311 | -1.606*** | 0.352 | 0.202 |

*Notes.* SMU = social media use; *B* = logit coefficient; *SE* = standard error; *OR* = Odds ratio.
*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

**Table A7.5**

*Multinomial Regression, Membership Class 1, 2, 3, and 4 (n = 1,419)*

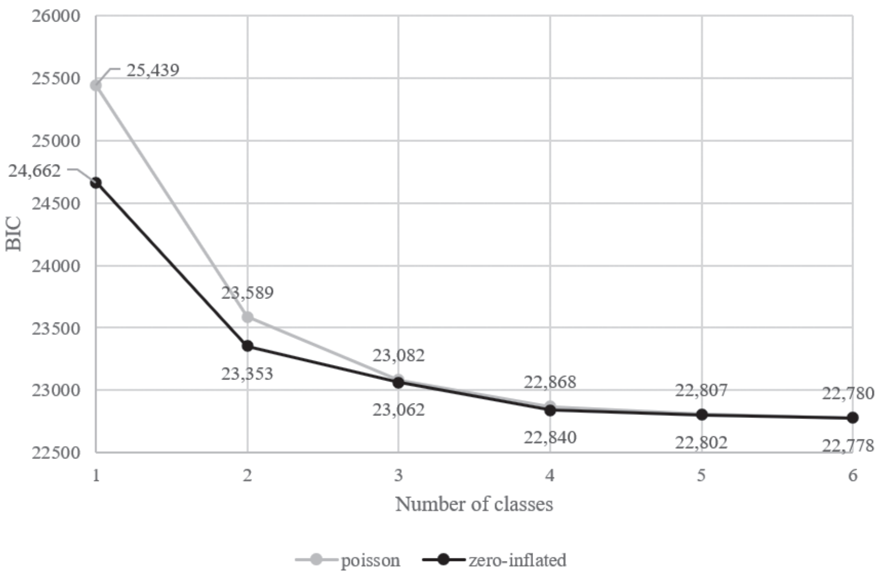
| | **Class 1: Variably high problematic SMU, variably high SMU frequency** | | | **Class 2: Persistently high problematic SMU, persistently average SMU frequency** | | | **Class 3: Persistently low problematic SMU, persistently low SMU frequency** | | | **Class 4: Persistently low problematic SMU, variably high SMU frequency** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Ref. = c2** | **Ref. = c3** | **Ref. = c4** | **Ref. = c1** | **Ref. = c3** | **Ref. = c4** | **Ref. = c1** | **Ref. = c2** | **Ref. = c4** | **Ref. = c1** | **Ref. = c2** | **Ref. = c3** |
| **Controls** | | | | | | | | | | | | |
| Girl (ref. = boy) | 1.674*** | 2.321*** | 1.174*** | -1.674*** | 0.647* | -0.500 | -2.321*** | -0.647* | -1.147*** | -1.174*** | 0.500 | 1.147*** |
| Pre-vocational education (ref. = pre-university) | 1.150* | 2.078*** | 1.445** | -1.150* | 0.927* | 0.294 | -2.078*** | -0.927* | -0.633* | -1.445** | -0.294 | 0.633* |
| Intermediate education (ref. = pre-university) | 0.309 | 1.132* | 0.499 | -0.309 | 0.823 | 0.190 | -1.132* | -0.823 | -0.633* | -0.499 | -0.190 | 0.633* |
| Immigrant background (ref. = non-immigrant) | -0.420 | -0.172 | 0.100 | 0.420 | 0.248 | 0.520 | 0.172 | -0.248 | 0.272 | -0.100 | -0.520 | -0.272 |
| **Subjective wellbeing** | | | | | | | | | | | | |
| Life satisfaction | -0.556 | -0.881* | -1.349*** | 0.556 | -0.325 | -0.793* | 0.881* | 0.325 | -0.468 | 1.349*** | 0.793* | 0.468 |
| Self-esteem | 0.330 | -0.243 | 0.638 | -0.330 | -0.573 | 0.309 | 0.243 | 0.573 | 0.881** | -0.638 | -0.309 | -0.881** |
| **Self-control** | | | | | | | | | | | | |
| Attention deficit | 0.509 | 1.048* | 1.050** | -0.509 | 0.539 | 0.541 | -1.048* | -0.539 | 0.002 | -1.050** | -0.541 | -0.002 |
| Impulsivity | 1.833*** | 3.667*** | 1.607*** | -1.833*** | 1.834*** | -0.226 | -3.667*** | -1.834*** | -2.060*** | -1.607*** | 0.226 | 2.060*** |
| **Social competencies** | | | | | | | | | | | | |
| Perceived friendship competence | 2.424*** | 1.396** | -0.210 | -2.424*** | -1.028* | -2.634*** | -1.396** | 1.028* | -1.606*** | 0.210 | 2.634*** | 1.606*** |

*Note.* SMU = social media use; Ref. = reference category; c = class. All estimates denote logit coefficients;
*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

7

**Figure A7.1**

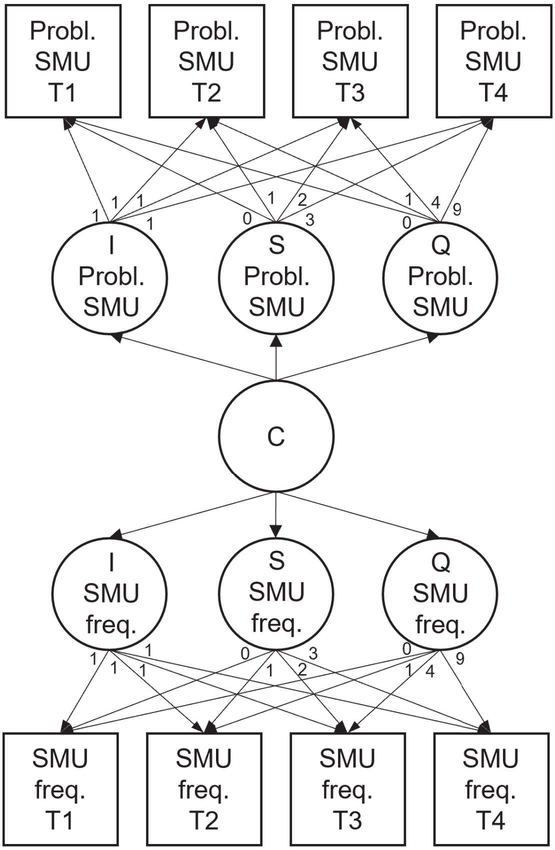
*BIC-Model Fit of the (Zero-Inflated) Poisson LCGMs with 1 to 6 Classes, n = 1,419*




*Notes.* BIC = Bayesian Information Criterion (BIC). Latent class growth models (LCGMs) include the co-trajectories of problematic social media use and social media use frequency.

**Figure A7.2**

*Model Specification of the Parallel Latent Class Growth Model*




*Notes.* Probl. SMU = problematic social media use; SMU freq. = social media use frequency; I = intercept; S = slope; Q = quadratic slope; C = latent class. Circles denote latent variables. Squares denote observed variables. Numbers indicate the values of the constrained factor loadings.

# CHAPTER 8

# THE COMPLEX ASSOCIATION BETWEEN SOCIAL MEDIA USE INTENSITY AND ADOLESCENT WELLBEING: A LONGITUDINAL INVESTIGATION OF FIVE FACTORS THAT MAY AFFECT THE ASSOCIATION

Maartje Boer, Gonneke W. J. M. Stevens, Catrin Finkenauer, and Regina J. J. M. van den Eijnden

**Author Contributions**

All authors conceived of the study. MB conducted the literature review, data analyses, and drafted the initial and revised manuscript. RvdE initiated and coordinated the data collection of the data from the present study. GS, CF, and RvdE critically reviewed all sections of the initial and revised manuscript and advised during all stages of the manuscript preparation. All authors approved of the final manuscript.

**Publication**

Boer, M., Stevens, G. W. J. M., Finkenauer, C., & Van den Eijnden, R. J. J. M. (2022). The complex association between social media use intensity and adolescent wellbeing: A longitudinal investigation of five factors that may affect the association. *Computers in Human Behavior* , *128*, 107084. https://doi.org/10.1016/j.chb.2021.107084

# Abstract

The present study examined five possible explanations for the mixed findings on the association between adolescents' social media use (SMU) intensity and wellbeing. Particularly, it investigated whether the association between SMU intensity and life satisfaction depended on (1) the type of SMU activity the adolescent engaged in, (2) the (non)linearity of the association, (3) individual differences, (4) inclusion of SMU problems, and (5) the level of analysis. Data from four waves of longitudinal data among 1,419 adolescents were used ($M_{age(T1)}$ = 12.51 (0.60), 45.95% girl). Multilevel analyses showed that at the within-person level, on average, changes in different types of SMU activities were not associated with changes in life satisfaction. Within individuals, the associations ranged from negative to positive across adolescents. In general, this variation could not be explained by adolescents' engagement in upward social comparisons. At the between-person level, the higher adolescents' average intensity of certain SMU activities, the lower their average level of life satisfaction. However, these associations were confounded by adolescents' SMU problems. No curvilinear associations were found. Overall, the findings underline that to enhance our understanding of the association between SMU and wellbeing in adolescence, it is important to acknowledge the heterogeneity of effects, distinguish between SMU intensity and SMU problems, and disentangle within- from between-person effects.


*Keywords*: Social media use, wellbeing, life satisfaction, adolescents, longitudinal study.

# The Complex Association Between Social Media Use Intensity and Adolescent Wellbeing: A Longitudinal Investigation of Five Factors That May Affect the Association

Most adolescents spend a lot of time on social media nowadays, which raises concerns among many (Griffiths & Kuss, 2011). Social media refer to social network sites (SNS) and instant messengers (IM), such as Instagram and WhatsApp, respectively. Some researchers suggest that high levels of social media use (SMU) intensity are detrimental to adolescents' wellbeing, for instance to their life satisfaction (Kelly et al., 2018; Twenge, Martin, et al., 2018). Other scholars suggest that the association between SMU intensity and wellbeing is more complex, however (Dienlin & Johannes, 2020). Review studies highlight that the overall association is weak, and that the direction and strength of the association is contingent on many theoretical and methodological factors, including the conceptualization of SMU and the used analytical approach (Meier & Reinecke, 2020; Odgers & Jensen, 2020; Orben, 2020a). Nevertheless, factors that may affect the association between SMU intensity and wellbeing are typically studied in isolation, painting an incomplete picture of the association. To enhance knowledge on the association between adolescents' SMU intensity and wellbeing, the current study examined five factors that may affect this association. Using four waves of longitudinal data among Dutch secondary school adolescents, the current study tested how these five factors jointly affect the association between adolescents' SMU intensity and wellbeing.



## The Association Between SMU Intensity and Wellbeing Depends on the Type of SMU Activity the Adolescent Engages In

Adolescents' overall *SMU intensity* encompasses their intensity of engagement in different SMU activities, that is, their active and passive SMU. *Active SMU* refers to communication and content creation on social media, for example posting messages or photos on social media or chatting with others. *Passive SMU* refers to viewing other people's messages or photos on social media and scrolling through social media feeds. Research suggests that active SMU is beneficial to adolescents' wellbeing, whereas passive SMU is detrimental

(Verduyn et al., 2017). Presumably, active SMU enhances one's social network, which may increase social capital and feelings of connectedness. Conversely, because people tend to present themselves in an overly appealing way on social media, passive SMU implicates exposure to unrealistically flattering portrayals of others. This exposure may induce feelings of envy or upward social comparisons, such as the perception that others are more successful (Verduyn et al., 2017).

The proposition that particularly passive SMU is detrimental to wellbeing has received empirical support. A meta-analysis showed that passive SMU was negatively associated with indicators of wellbeing, whereas active SMU was positively associated with wellbeing, albeit both with small effect sizes (Liu et al., 2019). Recent experience sampling studies with multiple daily assessments challenge these results (Beyens, Pouwels, Valkenburg, et al., 2020; Beyens, Pouwels, Van Driel, et al., 2020; Jensen et al., 2019). Particularly, one study found that, on average, moments when adolescents had used Instagram or WhatsApp passively were associated with moments of increased affective wellbeing. In contrast, moments of active use of Instagram or WhatsApp were not associated with changes in wellbeing (Beyens, Pouwels, Valkenburg, et al., 2020). Another study found that, on days when adolescents showed increased levels of passive SMU or active SMU, adolescents did not report daily changes in depression or worries (Jensen et al., 2019). Similarly, a study that distinguished between the intensity of passive public (i.e., viewing posts or stories of others), passive private (i.e., reading direct messages), and active private (i.e., sending direct messages) SMU showed that, on average, neither of the three SMU activities predicted immediate changes in wellbeing (Beyens, Pouwels, Van Driel, et al., 2020). Overall, while meta-analytic results suggest that passive SMU is detrimental, and that active SMU is beneficial to wellbeing, recent studies using intensive daily measurements question the robustness of this finding.

## The Association Between SMU Intensity and Wellbeing May or May Not Be Linear

According to the 'Goldilocks hypothesis', the association between adolescents' SMU intensity and wellbeing is curvilinear (Dienlin & Johannes, 2020; Przybylski & Weinstein, 2017). Specifically, in contemporary society where (social) media are integrated into the daily lives of many young people, both very little as well as excessive SMU may be harmful to wellbeing. Adolescents who barely use social media may miss out on social information and interaction with peers, while adolescents who use social media excessively may displace meaningful offline activities to online activities. In contrast, moderate SMU may not be harmful and could even be advantageous to adolescent wellbeing (Przybylski & Weinstein, 2017). Therefore, the association between SMU intensity and wellbeing may show an inverted u-shape.

Cross-sectional research supports this hypothesis by showing that adolescents who do not use social media and those who use it excessively report lower levels of happiness and overall mental wellbeing than those who use it moderately (Przybylski & Weinstein, 2017; Twenge, Martin, et al., 2018). However, longitudinal research does not support this hypothesis. Specifically, a longitudinal study on the association between overall screen time and depressive symptoms did not find any differences in the association across groups of adolescents below or above certain thresholds of screen time (Houghton et al., 2018). In addition, an experience sampling study did not yield curvilinear associations over time between several social media activities and depression or worry, except for active SMU: In line with the Goldilocks hypothesis, on days when adolescents did not create or created a lot of content on social media, they reported increased depressive symptoms, whereas on days when they created some content, they reported decreased depressive symptoms (Jensen et al., 2019). Nevertheless, the researchers emphasized that this finding should be interpreted with caution, because very few adolescents created a lot of content on one day (Jensen et al., 2019). Thus, while cross-sectional research supports the Goldilocks hypothesis, longitudinal and experience sampling studies hardly replicate these findings.

8

## The Association Between SMU Intensity and Wellbeing Depends On Individual Differences

Some adolescents may be negatively affected by high SMU intensity, some positively, and some may not be affected at all. Therefore, researchers increasingly advocate for studying *heterogeneity* in the association between adolescents' SMU intensity and wellbeing (Beyens, Pouwels, Valkenburg, et al., 2020; Odgers et al., 2020; Orben, 2020a). According to the Differential

Susceptibility to Media effects Model (DSMM), media effects depend on individuals' susceptibility to media effects (Valkenburg & Peter, 2013). One characteristic that may make individuals more susceptible to media effects may be adolescents' tendency to compare themselves to others, that is, their *social comparison tendency*. The 'social comparison perspective' posits that for adolescents who are sensitive to social comparison, exposure to others' messages on social media leads to decreased wellbeing through feelings of envy (De Vries et al., 2018). According to the 'emotional contagion perspective', adolescents who do not have this sensitivity may take over the positive emotions they encounter on social media, which may lead to increased wellbeing (De Vries et al., 2018). It has been argued that this moderating effect occurs when adolescents engage in *upward* social comparison, that is, when they evaluate others as superior (Verduyn et al., 2020). Thus, SMU activities may negatively or positively affect wellbeing, depending on adolescents' upward social comparison tendency.

Recent experience sampling studies confirm that adolescents strongly differ in their susceptibility to SMU effects (Beyens, Pouwels, Valkenburg, et al., 2020; Beyens, Pouwels, Van Driel, et al., 2020; Valkenburg, Beyens, et al., 2021). For example, one study showed that momentary associations between adolescents' intensity of passive and active SMU activities and affective wellbeing ranged from a moderate negative to a moderate positive association across adolescents (Beyens, Pouwels, Van Driel, et al., 2020). In an experimental study, adolescents with a strong social comparison tendency were negatively affected by exposure to positively framed Instagram posts. In contrast, adolescents who lacked this tendency were positively affected by exposure to such posts (De Vries et al., 2018). A cross-sectional study indicated that among adolescents with a low social comparison tendency, there was a negative association between their intensity of active Instagram use and their level of loneliness. However, among adolescents with a high social comparison tendency, no association between active Instagram use and loneliness was found (Yang, 2016). Overall, these studies suggest that the association between SMU activities and wellbeing depend on adolescents' sensitivity for (upward) social comparison.

## The Association Between SMU Intensity and Wellbeing Depends On Whether SMU Problems Are Considered

Adolescents' SMU intensity refers to the frequency or time spent on SMU activities, while SMU problems are characterized by symptoms of addiction to social media, for example, loss of control over SMU (Griffiths et al., 2014). SMU intensity is correlated with SMU problems with a small to moderate effect size (Frost & Rickwood, 2017; Parry et al., 2020). Longitudinal research using the same data as the present study shows that although many adolescents with SMU problems report high SMU intensity, most adolescents show high SMU intensity without any SMU problems and that some adolescents who report SMU problems do not show high SMU intensity (Boer, Stevens, Finkenauer, & Van den Eijnden, 2021). Rather than higher levels of SMU intensity, higher levels of SMU problems may be detrimental to adolescents' wellbeing (Primack et al., 2017; Van den Eijnden et al., 2018). Adolescents engaging in high SMU intensity may be well able to regulate their SMU and to combine it with a healthy lifestyle. In contrast, when adolescents experience SMU problems, which means that SMU dominates their everyday life and impairs control over thoughts and behaviors, this may threaten their wellbeing. Given that SMU intensity and SMU problems are correlated, but could have differential associations with wellbeing, observed negative associations between SMU intensity and wellbeing may be driven by SMU problems.

Notwithstanding the previous reasoning, few studies included both indicators of SMU in their analyses. Previous longitudinal research using data from the present study showed that, when controlled for SMU problems, adolescents' overall SMU intensity did not predict changes in life satisfaction and depressive symptoms over time. Furthermore, SMU problems predicted decreases in life satisfaction and increases in depressive symptoms (Boer, Stevens, Finkenauer, De Looze, et al., 2021; Van den Eijnden et al., 2018). Also, in a cross-sectional study among adolescents from 29 countries, intensive communication on social media was not associated with life satisfaction, whereas problematic SMU was negatively associated with life satisfaction (Boer, Van den Eijnden, et al., 2020). A limitation of these studies is that they did not compare the association between SMU intensity and wellbeing with and without controlling for SMU problems. Hence, it remained unclear whether the association between SMU intensity and indicators of wellbeing was confounded by SMU problems. Research overcoming this limitation showed that adolescents' time spent on SMU was associated with depressive symptoms in a bivariate model, but this association disappeared when controlling for SMU problems (Shensa et al., 2017). Overall, the few studies including both SMU intensity and SMU problems suggest that SMU problems are negatively associated with wellbeing, while SMU intensity is not.

## The Association Between SMU Intensity and Wellbeing Depends On the Level at Which It Is Being Analyzed

Alongside the abovementioned four more theoretical factors, the association between SMU intensity and wellbeing may also depend on methodological factors. Many studies on the association between SMU intensity and wellbeing, including review studies, rely on cross-sectional data (Odgers & Jensen, 2020; Orben, 2020a). Cross-sectional data are more likely to reflect associations at the *between-person level* than at the *within-person level*. Between-person associations reveal whether adolescents who report higher SMU intensity report lower levels of wellbeing *relative to adolescents* who report lower SMU intensity. Longitudinal data allow for testing both within- and between person associations, although many longitudinal studies did not make this distinction (Coyne et al., 2020). Within-person associations reflect the processes occurring within the individual adolescent. These associations denote whether changes in SMU intensity *relative to one's individual average level* of SMU intensity are associated with changes in wellbeing relative to one's individual average level of wellbeing. It is not uncommon that within-person associations differ from between-person associations; not only in effect size, but also in direction (Dienlin & Johannes, 2020; Hamaker, 2012; Orben, 2020a).

Several longitudinal studies showed small to moderate negative associations between the intensity of SMU activities and indicators of wellbeing (e.g., internalizing problems, life satisfaction) at the between-person level, while there were no or very small associations at the within-person level (Beeres et al., 2020; Coyne et al., 2020; Jensen et al., 2019; Orben et al., 2019; Stavrova & Denissen, 2020). In two other longitudinal studies, adolescents' overall SMU intensity or text messaging was not associated with internalizing problems, depressive symptoms, and life satisfaction, neither at the between-person nor at the within-person level (George et al., 2020; Schemer et al., 2020).

In another longitudinal study, overall SMU intensity was positively related to depression and negatively to self-esteem, both at the between-person and within-person level, but effect sizes were not reported (Boers et al., 2019). Thus, most studies that separate within-person from between-person variance show no or a negligible negative association at the within-person level, while the association at the between-person level is more inconsistent.

## Current Study

Findings on the association between SMU intensity and wellbeing are conflicting. Based on the existing literature, we identified five theoretical and methodological factors that may explain these inconsistencies. Translating these factors into research questions (RQs), the present study investigated:

- RQ1: Which type of SMU activity is negatively associated with adolescent wellbeing?
- RQ2: Is the association between SMU intensity and wellbeing non-linear?
- RQ3: (a) Does the association between SMU intensity and wellbeing differ across adolescents and if so, (b) can these differences be explained by adolescents' tendency to engage in upward social comparisons?
- RQ4: Is the negative association between SMU intensity and wellbeing confounded by SMU problems?
- RQ5: Does the negative association between SMU intensity and wellbeing occur at the within-person and/or between-person level?

These research questions have mostly been examined in isolation. Therefore, it remains unknown whether and how they affect the association between SMU intensity and wellbeing when being considered in concert. This is important to improve our understanding of possible SMU effects on adolescent wellbeing and to fuel specific directions for future research. To study our research questions, we used four waves of longitudinal data with yearly time intervals among Dutch secondary school adolescents (*n* = 1,419). We examined adolescents' SMU intensity using self-reported SMU frequencies and wellbeing using self-reported life satisfaction. While the scientific discourse on SMU effects often focuses on a dichotomy between active and passive SMU activities, the present study distinguished six SMU activities that ranged from more active (e.g., posting messages on SNS) to more passive (e.g., viewing messages on SNS).

# Methods

## Data

We used data from the Digital Youth (DiYo) project, which is a longitudinal survey with yearly time intervals among Dutch secondary school adolescents, conducted in 2015 until 2019 (Van den Eijnden et al., 2018). The survey assessed self-report internet-related behaviors and wellbeing. For the present study, we selected four waves of data from adolescents who were in 7$^{th}$ grade at time of the 2015 ($n$ = 1,352) or 2016 ($n$ = 998) survey assessments. Adolescents who had repeated a class ($n$ = 46) or who participated in less than two waves ($n$ = 885) were excluded, which yielded an analysis sample of 1,419 adolescents. The proportion of boys, pre-vocational educated adolescents, and adolescents with an immigrant background was higher among excluded adolescents than among included adolescents. However, these differences were very small (Cramer's $V$ < 0.109). In addition, excluded adolescents reported lower life satisfaction at T1 until T3, higher SNS posting intensity at T1 and T2, higher SNS and IM viewing intensity at T1, lower levels of upward social comparison at T2, and more SMU problems at T1 until T3, as compared to included adolescents. Again, these differences were small (Cohen's $D$ range = 0.151 to 0.368).

Adolescents in the analysis sample ($n$ = 1,419) were on average 12.51 years at T1 ($SD$ = 0.60), 45.95% was female, and 21.86% had an immigrant background. In the Dutch education system, adolescents are enrolled in different educational levels from 12 years onwards (i.e., when transitioning to secondary school), namely pre-vocational, intermediate, and pre-university level (57.79%, 28.54%, and 13.67%, respectively in the present study). The distributions of female adolescents and adolescents with an immigrant background in our study were approximately similar to the distributions in the 13- to 16-year-old population in the Netherlands in 2018/2019 (Central Bureau for Statistics, 2021). Adolescents enrolled in the pre-vocational educational level were slightly overrepresented (57.79% vs. 49.42%) and adolescents enrolled in the pre-university educational level were slightly underrepresented (13.67% vs. 20.62%) in our study (Central Bureau for Statistics, 2021).

In T1, 44.89% of the analysis sample did not participate. In T2, this was 6.48%, in T3 24.10% and in T4 65.12%. Dropout in T1 was due to the fact that adolescents who entered the study after T1 were also included in the sample.

The high dropout rate in T4 was mainly due to dropout of entire pre-vocational schools, school years, and school classes, for example because the survey assessment could not be scheduled due to practical constraints. Hence, the dropout was not related to individual selection.

Parents of participating adolescents were provided with the opportunity to refuse participation of their child. Adolescents were informed that their participation was anonymous and voluntary, and that they could withdraw their participation at any time. The survey assessment took place in the classroom setting through digital self-completion under supervision of research assistants. The assessments were carried out in accordance with the Declaration of Helsinki and approved by the board of ethics of Utrecht University (FETC16-076 Eijnden).

## Measures

### *Life Satisfaction*

Life satisfaction was measured using the 7-item Student's Life Satisfaction Scale (Huebner, 1991). Respondents were asked about their thoughts around their own life, for example: 'My life is going well' and 'I have what I want in life'. Response options ranged from (1) *strongly disagree* to (6) *strongly agree*. A mean score was computed that denoted adolescents' life satisfaction. Cronbach's alpha was 0.83.



### *SMU Intensity*

We distinguished four SNS and two IM activities, each measured with one item (Van den Eijnden et al., 2018). SNS intensity was indicated by *SNS viewing* ('How many times *per day* do you view social network sites?'), *SNS posting* ('How many times *per week* do you post a message, photo, or video on social network sites?'), *SNS liking* ('How many times *per week* do you 'like' messages, photos, or videos of others on social network sites?'), and *SNS responding* ('How many times *per week* do you respond to messages, photos, or videos on social network sites?'). Response options ranged from (1) *never or less than once* to (7) *more than 40 times*. The questionnaire presented examples of SNS including 'Facebook, Twitter, Instagram, Google+, or Pinterest, but not WhatsApp or SnapChat'. Regarding IM intensity, we assessed *IM viewing*

(‘How many times *per day* do you check your smartphone to see whether you have received a message?’), and *IM sending* (‘How many times *per day* do you send a message, photo or video via your smartphone?’). Response options ranged from (1) *never or less than once* to (7) *more than 80 times*. The questionnaire presented examples of IM, including ‘WhatsApp, Chat, SnapChat, or SMS’. SNS posting was considered the most *active SMU activity*, followed by IM sending, SNS responding, and SNS liking. This is because SNS posting involves self-broadcasting messages, photos, or videos to a large public audience. IM sending involves sending personalized messages, photos, or videos to specific persons or private groups. SNS responding typically involves brief responses to other people’s posts. SNS liking includes one-click feedback on other people’s posts or responses. SNS viewing was considered the most *passive SMU activity*, followed by IM viewing. This is because SNS viewing involves browsing other people’s posts or reading news feed, whereas IM viewing has a more social component because it involves reading received personalized messages.

### *Social Comparison*

Social comparison was measured using a newly developed 5-item scale on social comparison during SMU. Specifically, the scale examined *upward social comparison* during SMU, because upward comparisons are regarded to elicit greater sensitivity to SMU effects than downward or general comparison behaviors (Verduyn et al., 2020). Respondents were asked ‘How often do you have the following thoughts when viewing your peers’ messages, photos, and videos on social network sites?’, followed by: ‘He or she does more fun things than I do’, ‘He or she has more friends than I do’, ‘He or she is more popular than me’, ‘He or she received more ‘likes’ than me’, and ‘He or she looks better than I do’, with responses ranging from (1) *never* to (5) *very often*. Cronbach’s alpha was 0.88.

### *Controls*

We controlled for SMU problems, gender, educational level, and immigrant background. We used the 9-item Social Media Disorder-Scale to assess adolescents’ *SMU problems* (Boer, Stevens, Finkenauer, Koning, et al., 2021; Van den Eijnden et al., 2016). The items correspond to the nine criteria for internet gaming disorder as established in the appendix of the Diagnostic and Statistical Manual of Mental Disorders, including preoccupation, tolerance, withdrawal, persistence, displacement, problems, deception, escape, and conflict (American Psychiatric Association, 2013; Lemmens et al., 2015). Respondents were asked: 'During the past year, have you (…)', followed by, for example, 'often felt bad when you could not use social media?' (withdrawal). Response options were (1) *yes* and (0) *no*. A sum-score was computed that denoted adolescents' number of present criteria. As appropriate for dichotomous items, internal consistency was calculated using the tetrachoric correlation matrix (Gadermann et al., 2012), which yielded an alpha of 0.85.

Respondents' *gender* was measured by asking whether they were (0) *boy* or (1) *girl*. Also, adolescents reported their *educational level:* (1) *pre-vocational*, (2) *intermediate*, or (3) *pre-university*. Adolescents' educational level was defined as their most recent reported educational level. *Immigrant background* was determined based the reported country of origin of the parents.

Table 8.1 shows the descriptive statistics of all study variables.



**Table 8.1**
*Descriptive Statistics*

| | Mean / proportion | *SD* | Min. | Max. | *n* |
|---|---|---|---|---|---|
| **Time variant variables** | | | | | |
| Life satisfaction | 4.664 | 0.842 | 1 | 6 | 5,676 |
| SNS viewing | 4.190 | 1.675 | 1 | 7 | 5,676 |
| SNS posting | 1.980 | 1.457 | 1 | 7 | 5,676 |
| SNS liking | 4.950 | 2.089 | 1 | 7 | 5,676 |
| SNS responding | 3.450 | 1.925 | 1 | 7 | 5,676 |
| IM viewing | 4.454 | 1.575 | 1 | 7 | 5,676 |
| IM sending | 4.259 | 1.732 | 1 | 7 | 5,676 |
| Upward social comparison | 1.841 | 0.815 | 1 | 5 | 5,676 |
| SMU problems | 1.186 | 1.519 | 0 | 9 | 5,676 |
| **Time invariant variables** | | | | | |
| Girl | 0.459 | | 0 | 1 | 1,419 |
| Pre-vocational education | 0.578 | | 0 | 1 | 1,419 |
| Immigrant background | 0.219 | | 0 | 1 | 1,419 |

*Notes*. SNS = social network sites; IM = instant messenger; SMU = social media use; *SD* = standard deviation; Min. = minimum; Max. = maximum; *n* = sample size.

## Analytical Approach

### *Missing Data*

Missing data ranged between 6.55% (SMU intensity T2) and 67.94% (upward social comparison T4). Little's Chi-square test for missing data showed that the data were not completely missing at random ($\chi^2(2{,}564) = 3073.68$, $p < 0.001$). To overcome potential bias that is often associated with listwise deletion of respondents when data are not missing completely at random, missing data were imputed using multiple imputation by chained equations using Stata 13.0 (Royston & White, 2011; StataCorp, 2013). Particularly, missing data were imputed based on available data on the study variables in other waves with the data in 'wide format' ($n$ = 1,419). Multiple imputation is considered to reduce potential bias related to missing data even when the percentage of missing data is very high (Madley-Dowd et al., 2019). We conducted five imputations, which were based on predictive mean matching using the five nearest observations. As such, all 1,419 respondents were retained for the analyses.

### *Data Organization*

After imputation, data were restructured into 'long format'. That is, observations reflected repeated measures (i.e., level 1, within-person level: $n$ = 5,676), which were nested in adolescents (i.e., level 2, between-person level: $n$ = 1,419). Subsequently, to examine SMU activities and SMU problems and their associations with life satisfaction on both levels, we computed adolescents' person-specific means of SMU activities and SMU problems based on their respective repeated measures. Also, we computed adolescents' person-specific means of upward social comparison to test whether these means explained potential individual differences in the within-person associations between SMU activities and life satisfaction. Subsequently, the repeated measures of adolescents' SMU activities and SMU problems were centered using their computed person-specific mean (Wang & Maxwell, 2015). Due to this centering, associations on the first level denote, for example, whether changes in SNS viewing intensity relative to one's average SNS viewing intensity were associated with changes in life satisfaction relative to one's average life satisfaction. The continuous time-invariant predictors (i.e., average SNS viewing) and the moderator (i.e., upward social comparison) were centered using the grand mean. Associations on the second level reflect, for example, whether adolescents with higher means in SNS viewing intensity reported higher means in life satisfaction than adolescents with lower means in SNS viewing intensity.

### *Modelling*

Next, the data were exported to Mplus 8.6 (L. K. Muthén & Muthén, 2017b) to conduct a series of multilevel models. First, fixed effects models were conducted to test the associations between the six different SMU activities and life satisfaction. Specifically, we estimated the within-person and between-person associations between adolescents' intensity of SMU activities and their life satisfaction, for each SMU activity separately (M1a-f). In these models, the within-person associations were constrained to be equal across adolescents. The models included 'wave' as a level-1 control variable to account for common time trends (Hox, 2010a; Wang & Maxwell, 2015). Also, we included gender, educational level, and immigrant background as level-2 control variables. This first series of models are referred to as the baseline models. To test whether the associations were confounded by SMU problems, we subsequently extended the baseline models with SMU problems as additional level-1 and level-2 control variable (M2a-f). In the next step, we extended the baseline models with quadratic terms for the SMU activities on both levels (M3a-f). Thereafter, we extended the quadratic models with SMU problems as additional control variable on both levels (M4a-f).



Further, we extended the baseline models with random slopes for the within-person associations between the six SMU activities and life satisfaction (M5a-f). As recommended for multilevel modeling, a covariance between the random slope and random intercept was specified (Hox, 2010d). When adding the random parameters significantly improved model fit, this indicated that the respective within-person association varied across adolescents. Model fit was evaluated based on the *deviance*, where lower values indicated better model fit. The difference in deviance was evaluated using a chi-square difference test, with a corrected *p*-value as appropriate for testing slope variance (Hox, 2010b; Stoel et al., 2006). Also, lower *Akaike Information Criterion* (AIC) and *Bayesian Information Criterion* (BIC) values indicated better model fit (Hox, 2010b). In addition, *95% prediction intervals* (PIs) were computed, which express the estimated range of the associations across adolescents (Hox, 2010d). Subsequently, these random effects models were extended with SMU problems as additional control variable on both levels (M6a-f). Continuing on the random effects models, we examined whether the variances of the within-person associations between the six SMU activities and life satisfaction were explained by adolescents' average level of upward social comparisons (M7a-f), after which we extended these models with SMU problems (M8a-f). All models were run and read with the *MplusAutomation*-package in RStudio 1.4.1106 (Hallquist & Wiley, 2018; RStudio Team, 2021).

To interpret effect sizes, coefficients in the fixed effects models (M1-4) were STDYX-standardized, whereby 0.1 denoted a small effect, 0.3 moderate, and 0.5 large (Cohen, 1988). All models were estimated using Maximum Likelihood estimation. Codes for all data handling, imputation of missing data, and analyses are publicly available at https://osf.io/3fn2s/.

# Results

## Bivariate Associations

The intra class correlations of the study variables ranged from 0.195 (SNS posting) to 0.453 (IM viewing). This means that 54.7 to 81.5 percent of the variance of the study variables was related to changes over time, which is considered substantial. Table 8.2 shows the correlations between the study variables. At the within-person level (level 1), adolescents' life satisfaction decreased over time, with an almost moderate effect size. The more active SMU activities showed different changes over time: While the intensity of SNS responding and SNS liking increased over time with (very) small effect size, SNS posting decreased over time with small effect size, and IM sending did not change over time. The intensity of more passive SMU activities, namely SNS and IM viewing, increased over time with moderate and small effect sizes, respectively. In addition, increased intensity of all SMU activities, except for SNS posting, were associated with decreased life satisfaction, but with very small effect sizes. Increased SMU problems were associated with decreased life satisfaction and increased intensity of all SMU activities except for SNS posting, with small to moderate effect sizes.

At the between-person level (level 2), the higher adolescents' average intensity of more passive SMU activities (i.e., SNS and IM viewing) and IM sending, the lower was their average level of life satisfaction, although effect sizes were small. The higher the adolescents' average level of upward social comparison, the lower was their average level of life satisfaction, with a large effect size. There was a moderate to large negative correlation between adolescents' average level of SMU problems and life satisfaction. For all six

**Table 8.2**
*Bivariate Associations*

| **Level 1, within-person level ($n$ = 1,419)** | **Life satisfaction** | | **SNS viewing** | | **SNS posting** | | **SNS liking** | | **SNS responding** | | **IM viewing** | | **IM sending** | | **Wave** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | ***r*** | ***SE*** | ***r*** | ***SE*** | ***r*** | ***SE*** | ***r*** | ***SE*** | ***r*** | ***SE*** | ***r*** | ***SE*** | ***r*** | ***SE*** | ***r*** | ***SE*** | | |
| SNS viewing | -0.08*** | 0.02 | | | | | | | | | | | | | | | | |
| SNS posting | 0.03 | 0.02 | 0.16*** | 0.03 | | | | | | | | | | | | | | |
| SNS liking | -0.05* | 0.02 | 0.43*** | 0.02 | 0.07*** | 0.02 | | | | | | | | | | | | |
| SNS responding | -0.06* | 0.03 | 0.40*** | 0.03 | 0.22*** | 0.02 | 0.46*** | 0.03 | | | | | | | | | | |
| IM viewing | -0.06** | 0.02 | 0.45*** | 0.02 | 0.08*** | 0.02 | 0.33*** | 0.02 | 0.30*** | 0.02 | | | | | | | | |
| IM sending | -0.06** | 0.02 | 0.31*** | 0.02 | 0.11*** | 0.03 | 0.28*** | 0.02 | 0.30*** | 0.03 | 0.54*** | 0.02 | | | | | | |
| Wave | -0.26*** | 0.03 | 0.29*** | 0.03 | -0.18*** | 0.03 | 0.14*** | 0.04 | 0.08* | 0.04 | 0.17*** | 0.02 | 0.06 | 0.03 | | | | |
| SMU problems | -0.17*** | 0.01 | 0.14*** | 0.03 | 0.04 | 0.03 | 0.10*** | 0.02 | 0.13*** | 0.02 | 0.19*** | 0.02 | 0.15*** | 0.03 | 0.02 | 0.03 | | |
| **Level 2, between-person level ($n$ = 5,676)** | **Life satisfaction** | | **SNS viewing** | | **SNS posting** | | **SNS liking** | | **SNS responding** | | **IM viewing** | | **IM sending** | | **Upward social comparison** | | **SMU problems** | |
| | ***r*** | ***SE*** | ***r*** | ***SE*** | ***r*** | ***SE*** | ***r*** | ***SE*** | ***r*** | ***SE*** | ***r*** | ***SE*** | ***r*** | ***SE*** | ***r*** | ***SE*** | ***r*** | ***SE*** |
| SNS viewing | -0.10* | 0.04 | | | | | | | | | | | | | | | | |
| SNS posting | -0.07 | 0.05 | 0.41*** | 0.05 | | | | | | | | | | | | | | |
| SNS liking | -0.06 | 0.04 | 0.69*** | 0.01 | 0.25*** | 0.04 | | | | | | | | | | | | |
| SNS responding | -0.06 | 0.04 | 0.69*** | 0.02 | 0.43*** | 0.04 | 0.69*** | 0.02 | | | | | | | | | | |
| IM viewing | -0.11** | 0.03 | 0.73*** | 0.02 | 0.38*** | 0.04 | 0.62*** | 0.02 | 0.60*** | 0.02 | | | | | | | | |
| IM sending | -0.10** | 0.03 | 0.63*** | 0.02 | 0.31*** | 0.03 | 0.56*** | 0.03 | 0.59*** | 0.02 | 0.76*** | 0.01 | | | | | | |
| Upward social comparison | -0.49*** | 0.03 | 0.19*** | 0.03 | 0.06 | 0.04 | 0.23*** | 0.03 | 0.22*** | 0.03 | 0.21*** | 0.03 | 0.20*** | 0.03 | | | | |
| SMU problems | -0.39*** | 0.03 | 0.35*** | 0.04 | 0.27*** | 0.03 | 0.24*** | 0.03 | 0.28*** | 0.04 | 0.37*** | 0.03 | 0.30*** | 0.03 | 0.42*** | 0.03 | | |
| | ***β*** | ***SE*** | ***β*** | ***SE*** | ***β*** | ***SE*** | ***β*** | ***SE*** | ***β*** | ***SE*** | ***β*** | ***SE*** | ***β*** | ***SE*** | ***β*** | ***SE*** | ***β*** | ***SE*** |
| Girl | -0.11* | 0.05 | 0.15*** | 0.04 | -0.01 | 0.04 | 0.21*** | 0.04 | 0.33*** | 0.04 | 0.10* | 0.04 | 0.14** | 0.04 | 0.27*** | 0.04 | 0.06 | 0.04 |
| Pre-vocational education | -0.01 | 0.05 | 0.19*** | 0.04 | 0.22*** | 0.04 | 0.05 | 0.04 | 0.16*** | 0.04 | 0.12** | 0.04 | 0.08* | 0.04 | -0.10* | 0.04 | 0.15*** | 0.04 |
| Immigrant background | 0.02 | 0.10 | 0.08 | 0.06 | 0.10 | 0.06 | -0.12* | 0.06 | 0.01 | 0.06 | -0.11 | 0.06 | -0.13* | 0.06 | -0.03 | 0.06 | 0.05 | 0.06 |

*Notes.* SNS = social network sites; IM = instant messengers; SMU = social media use; Level 1 = yearly measurements; Level 2 = adolescents; r = correlation (0.1 = small, 0.3 = moderate, 0.5 = large effect); SE = standard error; β = STDY-standardized coefficient (0.2 = small, 0.5 = moderate, 0.8 = large effect).
*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

SMU activities except for SNS posting, higher average SMU intensity was associated with higher averages in upward social comparison, with small to moderate effect sizes.

Girls reported lower averages in life satisfaction than boys. For all six SMU activities except for SNS posting, girls reported higher average SMU intensity than boys. Also, girls reported higher average levels of upward social comparison than boys. Except for SNS liking, adolescents attending pre-vocational education reported higher intensity of all SMU activities than adolescents attending intermediate or pre-university education. Adolescents attending pre-vocational education reported lower average levels of upward social comparison than adolescents attending other educational tracks. Adolescents with an immigrant background reported lower average intensity of SNS liking and IM sending than adolescents without an immigrant background.

## Associations Between SMU Intensity and Life Satisfaction

Table 8.3 shows the summary of the results from the baseline fixed effects models (see Table A8.1 from the Appendix for all model estimates). At the within-person level, for none of the SMU activities, changes in adolescents' SMU intensity were associated with changes in their life satisfaction, regardless of whether we controlled for SMU problems. At the between-person level, high averages in more passive SMU activities, namely SNS viewing and IM viewing, were associated with lower averages in life satisfaction, but with small effect sizes (M1a,e: $\beta$ = -0.084; $\beta$ = -0.106, respectively). Also, the higher adolescents' average level of IM sending, the lower their level of life satisfaction (M1f: $\beta$ = -0.087). Hence, the negative association between SMU intensity and wellbeing was not specific to either more passive or active SMU (**RQ1**). Furthermore, the negative associations were only observed at the between-person level (**RQ5**). However, when controlled for SMU problems, these between-person associations disappeared (M2a,e,f). These results suggest that the observed negative associations were confounded by SMU problems (**RQ4**). In addition, a sensitivity analysis was conducted where all SMU activities were simultaneously included in one model, while controlling for SMU problems. Also in this model, on both levels, no associations between any of the SMU activities and life satisfaction were found.

**Table 8.3**

*Summary Results of Fixed Effects Models, Life Satisfaction*

| | | Not controlled for SMU problems (M1) | | | | Controlled for SMU problems (M2) | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Level 1 (*n* = 1,419)** | **Model** | ***B*** | ***SE*** | ***p*** | ***β*** | ***B*** | ***SE*** | ***p*** | ***β*** |
| SNS viewing | a | -0.003 | 0.011 | 0.807 | -0.005 | 0.012 | 0.013 | 0.356 | 0.020 |
| SNS posting | b | -0.012 | 0.008 | 0.136 | -0.021 | -0.008 | 0.009 | 0.356 | -0.014 |
| SNS liking | c | -0.005 | 0.007 | 0.499 | -0.010 | 0.003 | 0.007 | 0.658 | 0.006 |
| SNS responding | d | -0.022 | 0.012 | 0.062 | -0.044 | -0.011 | 0.013 | 0.364 | -0.023 |
| IM viewing | e | -0.013 | 0.011 | 0.247 | -0.021 | 0.007 | 0.011 | 0.552 | 0.011 |
| IM sending | f | -0.025 | 0.012 | 0.046 | -0.043 | -0.011 | 0.013 | 0.385 | -0.019 |
| **Level 2 (*n* = 5,676)** | **Model** | ***B*** | ***SE*** | ***p*** | ***β*** | ***B*** | ***SE*** | ***p*** | ***β*** |
| SNS viewing | a | -0.036* | 0.018 | 0.048 | -0.084 | 0.022 | 0.017 | 0.192 | 0.051 |
| SNS posting | b | -0.040 | 0.026 | 0.127 | -0.069 | 0.017 | 0.029 | 0.554 | 0.029 |
| SNS liking | c | -0.015 | 0.013 | 0.258 | -0.044 | 0.016 | 0.014 | 0.238 | 0.048 |
| SNS responding | d | -0.013 | 0.016 | 0.420 | -0.035 | 0.027 | 0.016 | 0.080 | 0.072 |
| IM viewing | e | -0.046** | 0.015 | 0.002 | -0.106 | 0.016 | 0.016 | 0.299 | 0.037 |
| IM sending | f | -0.036** | 0.013 | 0.008 | -0.087 | 0.012 | 0.014 | 0.409 | 0.029 |

*Notes.* SNS = social network sites; IM = instant messengers; SMU = social media use; Level 1 = yearly measurements; Level 2 = adolescents; *B* = unstandardized coefficient; *SE* = standard error, *p* = *p*-value; ***β*** = STDYX-standardized coefficient. Variables with the same letter (a-f) were included in the same model. Models 1a-f were controlled by wave (level 1) and gender, educational level, and immigrant background (level 2). Models 2a-f extended model 1a-f with SMU problems as additional control variable on the first and second level.
*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

8

## Curvilinear Associations Between SMU Intensity and Life Satisfaction

Table 8.4 shows the summary of the fixed effects models extended with quadratic effects (see Table A8.2 from the Appendix for all model estimates). Results showed that neither at the within-person nor at the between-person level quadratic effects were significant, regardless of whether we controlled for SMU problems (M3a-f, M4a-f). For the within-person level, this means that in years when adolescents showed very low or very high SMU intensity relative to their individual average, adolescents reported equal levels of life satisfaction as in years when their SMU intensity was around their individual average. At the between-person level, it means that adolescents who showed much less or much more SMU intensity than other adolescents, reported equally high levels of life satisfaction as adolescents who showed moderate SMU intensity. Hence, no curvilinear associations between any of the SMU activities and life satisfaction were found (**RQ2**).

**Table 8.4**

*Summary Results of Fixed Effects Models with Quadratic Effects, Life Satisfaction*

| | | Not controlled for SMU problems (M3) | | | | Controlled for SMU problems (M4) | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Level 1 ($n$ = 1,419)** | **Model** | ***B*** | ***SE*** | ***p*** | **$\beta$** | ***B*** | ***SE*** | ***p*** | **$\beta$** |
| SNS viewing | a | -0.002 | 0.011 | 0.849 | -0.004 | 0.012 | 0.013 | 0.334 | 0.021 |
| SNS viewing^2 | a | 0.010 | 0.008 | 0.209 | 0.028 | 0.010 | 0.007 | 0.188 | 0.027 |
| SNS posting | b | -0.022 | 0.011 | 0.050 | -0.038 | -0.016 | 0.012 | 0.177 | -0.028 |
| SNS posting^2 | b | 0.010 | 0.007 | 0.140 | 0.040 | 0.009 | 0.007 | 0.238 | 0.034 |
| SNS liking | c | -0.004 | 0.007 | 0.574 | -0.008 | 0.004 | 0.007 | 0.588 | 0.008 |
| SNS liking^2 | c | 0.002 | 0.005 | 0.755 | 0.007 | 0.002 | 0.005 | 0.693 | 0.008 |
| SNS responding | d | -0.022 | 0.012 | 0.062 | -0.045 | -0.012 | 0.013 | 0.352 | -0.025 |
| SNS responding^2 | d | 0.008 | 0.006 | 0.201 | 0.030 | 0.008 | 0.005 | 0.159 | 0.029 |
| IM viewing | e | -0.014 | 0.012 | 0.231 | -0.021 | 0.006 | 0.012 | 0.584 | 0.010 |
| IM viewing^2 | e | -0.009 | 0.007 | 0.205 | -0.021 | -0.006 | 0.007 | 0.393 | -0.014 |
| IM sending | f | -0.024* | 0.012 | 0.049 | -0.043 | -0.010 | 0.013 | 0.408 | -0.018 |
| IM sending^2 | f | 0.005 | 0.009 | 0.608 | 0.014 | 0.006 | 0.009 | 0.481 | 0.020 |
| **Level 2 ($n$ = 5,676)** | **Model** | ***B*** | ***SE*** | ***p*** | **$\beta$** | ***B*** | ***SE*** | ***p*** | **$\beta$** |
| SNS viewing | a | -0.038* | 0.019 | 0.042 | -0.089 | 0.021 | 0.017 | 0.222 | 0.049 |
| SNS viewing^2 | a | -0.010 | 0.011 | 0.381 | -0.035 | -0.003 | 0.009 | 0.704 | -0.012 |
| SNS posting | b | -0.079* | 0.032 | 0.014 | -0.137 | -0.001 | 0.033 | 0.972 | -0.003 |
| SNS posting^2 | b | 0.021 | 0.019 | 0.268 | 0.063 | 0.006 | 0.018 | 0.750 | 0.017 |
| SNS liking | c | -0.014 | 0.015 | 0.357 | -0.042 | 0.018 | 0.015 | 0.226 | 0.053 |
| SNS liking^2 | c | <0.001 | 0.007 | 0.976 | 0.001 | 0.001 | 0.006 | 0.859 | 0.007 |
| SNS responding | d | -0.015 | 0.017 | 0.384 | -0.038 | 0.027 | 0.016 | 0.088 | 0.072 |
| SNS responding^2 | d | -0.003 | 0.008 | 0.693 | -0.013 | -0.008 | 0.009 | 0.384 | -0.031 |
| IM viewing | e | -0.047** | 0.015 | 0.002 | -0.107 | 0.018 | 0.016 | 0.261 | 0.042 |
| IM viewing^2 | e | <0.001 | 0.012 | 0.996 | <0.001 | 0.007 | 0.013 | 0.575 | 0.024 |
| IM sending | f | -0.035** | 0.013 | 0.009 | -0.087 | 0.013 | 0.015 | 0.374 | 0.031 |
| IM sending^2 | f | 0.001 | 0.010 | 0.925 | 0.003 | 0.005 | 0.009 | 0.576 | 0.018 |

*Notes.* SNS = social network sites; IM = instant messengers; SMU = social media use; Level 1 = yearly measurements; Level 2 = adolescents; *B* = unstandardized coefficient; *SE* = standard error, $p$ = $p$-value; $\beta$ = STDYX-standardized coefficient. Variables with the same letter (a-f) were included in the same model. Models 3a-f were controlled by wave (level 1) and gender, educational level, and immigrant background (level 2). Models 4a-f extended model 3a-f with SMU problems as additional control variable on the first and second level.
*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

## Individual Differences in the Associations Between SMU Intensity and Life Satisfaction

### *Individual Differences*

Table 8.5 summarizes the results of the random effect models, which allowed the within-person associations between the SMU activities and life satisfaction to vary across adolescents (see Table A8.3 from the Appendix for all model estimates). The models with random slopes improved model fit, because they

**Table 8.5**

*Summary Results of Random Effects Models, Within-Person Associations (Level 1), Life Satisfaction*

| | | Model estimates | | | | Model comparison[1] | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Not controlled for SMU problems** | **Model** | ***B*** | ***SE* (*B*)** | ***p*** | **Var.** | ***SE* (Var.)** | **Δ Par.** | **Δ Deviance** | **Δ Deviance $p^2$** | **Δ AIC** | **Δ BIC** | **LL-B** | **UL-B** | **LL-$\beta$** | **UL-$\beta$** |
| SNS viewing | 5a | -0.002 | 0.012 | 0.865 | 0.008 | 0.004 | 2 | -10.504** | 0.003 | -6.5 | 6.8 | -0.172 | 0.168 | -0.296 | 0.289 |
| SNS posting | 5b | -0.012 | 0.008 | 0.164 | 0.006 | 0.003 | 2 | -8.568** | 0.009 | -4.6 | 8.7 | -0.157 | 0.133 | -0.271 | 0.231 |
| SNS liking | 5c | -0.004 | 0.007 | 0.602 | 0.005 | 0.003 | 2 | -18.406*** | <0.001 | -14.4 | -1.1 | -0.145 | 0.137 | -0.303 | 0.288 |
| SNS responding | 5d | -0.021 | 0.012 | 0.065 | 0.006 | 0.002 | 2 | -17.342*** | <0.001 | -13.3 | -0.1 | -0.178 | 0.135 | -0.361 | 0.275 |
| IM viewing | 5e | -0.011 | 0.011 | 0.324 | 0.012 | 0.004 | 2 | -18.098*** | <0.001 | -14.1 | -0.8 | -0.226 | 0.203 | -0.349 | 0.314 |
| IM sending | 5f | -0.024 | 0.012 | 0.052 | 0.007 | 0.004 | 2 | -20.926*** | <0.001 | -16.9 | -3.6 | -0.182 | 0.135 | -0.320 | 0.237 |
| **Controlled for SMU problems** | **Model** | ***B*** | ***SE* (*B*)** | ***p*** | **Var.** | ***SE* (Var.)** | ***SE* (*B*)** | **Δ Deviance** | **Δ Deviance $p^2$** | **Δ AIC** | **Δ BIC** | **LL-B** | **UL-B** | **LL-$\beta$** | **UL-$\beta$** |
| SNS viewing | 6a | 0.012 | 0.013 | 0.344 | 0.006 | 0.004 | 2 | -8.726** | 0.008 | -4.7 | 8.6 | -0.140 | 0.165 | -0.242 | 0.284 |
| SNS posting | 6b | -0.008 | 0.009 | 0.396 | 0.005 | 0.004 | 2 | -8.914** | 0.007 | -4.9 | 8.4 | -0.145 | 0.130 | -0.253 | 0.226 |
| SNS liking | 6c | 0.004 | 0.007 | 0.613 | 0.005 | 0.002 | 2 | -15.502*** | <0.001 | -11.5 | 1.8 | -0.133 | 0.140 | -0.280 | 0.295 |
| SNS responding | 6d | -0.011 | 0.013 | 0.377 | 0.006 | 0.002 | 2 | -13.024** | 0.001 | -9.0 | 4.3 | -0.161 | 0.139 | -0.328 | 0.283 |
| IM viewing | 6e | 0.008 | 0.011 | 0.469 | 0.011 | 0.004 | 2 | -15.822*** | <0.001 | -11.8 | 1.5 | -0.198 | 0.215 | -0.308 | 0.334 |
| IM sending | 6f | -0.011 | 0.012 | 0.393 | 0.005 | 0.003 | 2 | -14.822*** | <0.001 | -10.8 | 2.5 | -0.153 | 0.132 | -0.271 | 0.233 |

*Notes.* SNS = social network sites; IM = instant messengers; SMU = social media use; *B* = unstandardized coefficient; *SE* = standard error, *p* = *p*-value; Δ = change relative to the baseline fixed effects models M1,2a-f ; Var. = variance of the slope; Par. = Number of free parameters; Deviance = -2*loglikelihood; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion; LL = 95% prediction interval lower limit; UL = 95% prediction interval upper limit; $\beta$ = STDYX-standardized coefficient. Models 5a-f were controlled by wave (level 1) and gender, educational level, and immigrant background (level 2). Models 6a-f extended model 5a-f with SMU problems as additional control variable on the first and second level. All models included a covariance between the random slope and random intercept.

[1] Models 5a-f were compared to Model 1a-f, respectively; Models 6a-f were compared to Models 2a-f, respectively.

[2] The *p*-value for the deviance was corrected to take into account the boundary of the slope variance parameter (Hox, 2010b; Stoel et al., 2006).

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

showed a significant decrease in the deviance relative to the baseline fixed effects models (M5a-f: deviance $p_{range}$ = < 0.001 to 0.009). Correspondingly, in all models, the AIC decreased (M5a-f $AIC_{range}$ = -16.9 to -4.6). In contrast, the BIC increased for two models (M5a,b: BIC = 6.8 and 8.7), suggesting that for these models the random slopes deteriorated model fit. However, given that for all models the majority of the indices, if not all, showed significant slope variance, the findings suggest that the within-person associations between all six SMU activities and life satisfaction varied across adolescents. Furthermore, the 95% PIs suggest that in all models, the associations ranged from moderate negative to moderate positive associations (M5a-f: LL-$\boldsymbol{\beta}_{range}$ = -0.361 to -0.271; UL-$\boldsymbol{\beta}_{range}$ = 0.231 to 0.314), which is considered substantial. This means that for some adolescents, increased intensity of a SMU activity was associated with decreased life satisfaction, whereas for others, increased intensity of a SMU activity was associated with increased life satisfaction (**RQ3a**). When controlled for SMU problems, the variances in the associations decreased somewhat (M6a-f). However, most of the fit indices indicated that there were still significant variances in the within-person associations between the SMU activities and life satisfaction.

### ***Differences by Upward Social Comparison***

Table 8.6 shows whether the observed variation in the within-person associations could be explained by adolescents' average level of upward social comparison (see Table A8.4 from the Appendix for all model estimates). All models showed that the higher the average level of upward social comparison, the lower was the average level of life satisfaction. A moderating effect of the average level of upward social comparison on the association between one of the indicators of SMU intensity and life satisfaction was found: Among adolescents who reported lower averages in upward social comparison, increases in SNS liking were associated with increases in life satisfaction, whereas among adolescents with higher averages in upward social comparison, increases in SNS liking were associated with decreases in life satisfaction (M7c: $B_{SNS\ liking}$ = -0.030*upward social comparison). This moderating effect was also found when controlling for SMU problems (M8c). However, the variance of the slope of SNS liking was not reduced by this moderation (M5/6c relative to M7/8c), which indicates that the explanatory power of upward social comparison in the variance of the association between SNS liking and life satisfaction is negligible. The associations between the other SMU activities and life satisfaction were not moderated by upward social comparison (M7/8a,b,d-f). Overall, we did not find (strong) evidence that individual differences in the association between SMU intensity and wellbeing were explained by adolescents' tendency to engage in upward social comparisons (**RQ3b**).

**Table 8.6**

*Summary Results of Random Effects Models with Upward Social Comparison as Moderator, Life Satisfaction*

| | | **Not controlled for SMU problems (M7)** | | | **Controlled for SMU problems (M8)** | | |
|---|---|---|---|---|---|---|---|
| **Level 1 (*n* = 1,419)** | **Model** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| SNS viewing | a | -0.002 | 0.011 | 0.862 | 0.013 | 0.013 | 0.339 |
| SNS posting | b | -0.012 | 0.008 | 0.159 | -0.008 | 0.009 | 0.389 |
| SNS liking | c | -0.005 | 0.007 | 0.509 | 0.003 | 0.007 | 0.709 |
| SNS responding | d | -0.021 | 0.012 | 0.076 | -0.011 | 0.013 | 0.403 |
| IM viewing | e | -0.011 | 0.011 | 0.320 | 0.008 | 0.012 | 0.472 |
| IM sending | f | -0.024 | 0.012 | 0.051 | -0.011 | 0.013 | 0.388 |
| **Level 2 (*n* = 5,676)** | **Model** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| SNS viewing | a | 0.005 | 0.017 | 0.785 | 0.031* | 0.016 | 0.046 |
| SNS posting | b | -0.014 | 0.024 | 0.558 | 0.014 | 0.026 | 0.599 |
| SNS liking | c | 0.019 | 0.013 | 0.136 | 0.031* | 0.013 | 0.021 |
| SNS responding | d | 0.023 | 0.016 | 0.139 | 0.040** | 0.015 | 0.009 |
| IM viewing | e | <0.001 | 0.015 | 0.992 | 0.028 | 0.015 | 0.059 |
| IM sending | f | 0.003 | 0.013 | 0.842 | 0.023 | 0.014 | 0.103 |
| **Cross-level interactions** | **Model** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| SNS viewing * upward social comparison | a | -0.006 | 0.019 | 0.745 | 0.002 | 0.018 | 0.926 |
| SNS posting * upward social comparison | b | -0.013 | 0.015 | 0.377 | -0.011 | 0.016 | 0.481 |
| SNS liking * upward social comparison | c | -0.030* | 0.013 | 0.025 | -0.027* | 0.013 | 0.035 |
| SNS responding * upward social comparison | d | -0.025 | 0.019 | 0.185 | -0.023 | 0.018 | 0.217 |
| IM viewing * upward social comparison | e | -0.007 | 0.018 | 0.684 | 0.002 | 0.018 | 0.929 |
| IM sending * upward social comparison | f | -0.024 | 0.017 | 0.153 | -0.019 | 0.017 | 0.263 |

*Notes.* SNS = social network sites; IM = instant messengers; SMU = social media use; Level 1 = yearly measurements; Level 2 = adolescents; *B* = unstandardized coefficient; *SE* = standard error, *p* = *p*-value; Variables with the same letter (a-f) were included in the same model. Models 7a-f were controlled by wave (level 1) and gender, educational level, and immigrant background (level 2). Also the main effect of upward social comparison was included (level 2). Models 8a-f extended model 7a-f with SMU problems as additional control variable on the first and second level. All models included a covariance between the random slope and random intercept.
*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

### Additional Findings

Models 7 and 8 yielded additional findings. Table 8.6 shows that the previously found negative between-person association between more passive (i.e., SNS viewing, IM viewing) and more active (i.e., IM sending) SMU activities and life satisfaction were not observed anymore when controlling for upward social comparison (M7a,e,f). Furthermore, when we controlled for both upward social comparison and SMU problems at the between-person level, we observed positive between-person associations between one more passive (i.e., SNS viewing) and some more active (i.e., SNS liking, SNS responding) SMU activities (M8a,c,d) and life satisfaction. Thus, SMU problems and upward social comparison may together suppress positive between-person associations between some SMU activities and life satisfaction.

## Discussion

The present study investigated the extent to which the association between SMU intensity and wellbeing is dependent on (1) the SMU activity adolescents engage in, (2) the (non)linearity of the association, (3) individual differences, (4) whether SMU problems are considered, and (5) the level of analyses. In doing so, we distinguished SMU activities ranging from more active (i.e., SNS posting, IM sending, SNS responding, SNS liking) to more passive (i.e., SNS viewing, IM viewing). Wellbeing was indicated by life satisfaction. At the within-person level, there was no average association between any of the SMU activities and life satisfaction, regardless of whether we controlled for SMU problems. However, the associations at the within-person level varied: For some adolescents, increases in SMU activities were associated with decreases in life satisfaction, whereas for others, increases in SMU activities were associated with increases in life satisfaction. In general, this variation could not be explained by adolescents' tendency to engage in upward social comparisons. At the between-person level, higher average intensity of some more passive activities (i.e., SNS and IM viewing) and one more active activity (i.e., IM sending) were associated with lower average life satisfaction with a small effect size. However, these associations disappeared when controlling for adolescents' average level of SMU problems. In addition, for none of the SMU activities, evidence was found that the association between SMU intensity and life satisfaction was curvilinear.

Our findings highlight the importance of three factors for understanding the association between SMU activities and wellbeing in adolescence. First, answering the question whether the association between SMU intensity and wellbeing differs across adolescents (**RQ3a**), our findings showed that within-person effects of SMU intensity ranged from positive to negative across adolescents. This result is in line with experience sampling studies showing that for some adolescents, momentary increases in the intensity of SMU activities were associated with momentary decreases in wellbeing, but for others with increases or no changes in wellbeing (Beyens, Pouwels, Valkenburg, et al., 2020; Beyens, Pouwels, Van Driel, et al., 2020). This study extends these findings as it revealed that also with annual assessments, associations between adolescents' intensity of SMU activities and life satisfaction varied across adolescents.

Second, answering the question whether a negative association between SMU intensity and wellbeing is driven by SMU problems (**RQ4**), our findings indicated that negative between-person associations between certain SMU activities and life satisfaction disappeared when controlling for SMU problems. These findings suggest that a negative association between SMU intensity and life satisfaction may be explained by the presence of SMU problems rather than by engagement in specific SMU activities. Therefore, earlier found negative associations between SMU intensity and wellbeing revealed in previous studies may have been driven by unobserved SMU problems (e.g., Kelly et al, 2018; Twenge et al, 2018). However, even after controlling for SMU problems, we found that the within-person associations between the SMU activities and life satisfaction ranged from negative to positive. Hence, for some adolescents, increases in SMU activities were associated with decreases in life satisfaction, which could not be attributed to increases in SMU problems.

Third, related to our question at which level a negative association between SMU intensity and wellbeing occurs (**RQ5**), we found no average associations at the within-person level, while there were negative associations at the between-person level (although only when not controlling for SMU problems). This finding demonstrates that between-level associations do not necessarily reflect within-person dynamics, which was also found in earlier longitudinal studies (Beeres et al., 2020; Coyne et al., 2020; Orben et al., 2019). Conceptually, this finding suggests that the observed between-person association between higher SMU intensity and lower wellbeing was not a causal relation, as changes in SMU intensity were not related to changes in wellbeing within an adolescent.

Above all, some of the factors affecting the association between SMU intensity and life satisfaction need to be considered in concert when understanding this association. As noted above, SMU problems confound the association between certain SMU activities and life satisfaction, but only with regards to between-person associations.

We also examined which type of SMU activity could be detrimental to wellbeing (**RQ1**). At the within-person level, we found no average associations between any of the SMU activities and life satisfaction, which aligns with findings from experience sampling studies (Beyens, Pouwels, Van Driel, et al., 2020; Jensen et al., 2019). At the between-person level, the observed negative associations between adolescents' intensity of engaging in SMU activities and life satisfaction were not specific to passive SMU activities, as proposed by researchers (Liu et al., 2019; Verduyn et al., 2017). In line with our findings, other studies also showed that adolescents' active as well as passive SMU activities were negatively correlated with their wellbeing at the between-person level (Beyens, Pouwels, Van Driel, et al., 2020). Passive and active SMU activities are possibly difficult to disentangle, because adolescents often engage in such SMU activities simultaneously (Valkenburg, Van Driel, et al., 2021). For example, responding to a message on an IM requires viewing that message first. Accordingly, our study showed very high correlations between IM sending and IM viewing at the between-person level. As such, their differential associations with wellbeing may be difficult to grasp, which may explain why in our study IM sending and IM viewing were both negatively related to life satisfaction. However, we stress that these negative associations disappeared when we controlled for SMU problems.

Based on the Goldilocks hypothesis (Przybylski & Weinstein, 2017), we also investigated whether the association between SMU intensity and wellbeing was nonlinear (**RQ2**) , which was not confirmed in our study. Findings of the present study are thereby consistent with other longitudinal studies that did not find curvilinear associations (Houghton et al., 2018; Jensen et al., 2019). Curvilinear associations were mainly found in cross-sectional studies (Przybylski & Weinstein, 2017; Twenge, Martin, et al., 2018), which could imply that the Goldilocks hypothesis applies to associations at the between-person level at one particular timepoint. Alternatively, earlier found curvilinear associations may have been country-specific. International research shows that the association between adolescents' SMU and wellbeing are susceptible to country-level factors, for example the extent to which social media are adopted among youth within society (Boer, Van den Eijnden, et al., 2020).

Further, we examined whether the association between adolescents' SMU intensity and wellbeing would depend on the tendency to engage in upward social comparisons (**RQ3b**). We found no evidence for this moderating effect, with one exception: Among adolescents reporting high levels of upward social comparison, increases in SNS liking were associated with decreases in life satisfaction, which supports the social comparison perspective (De Vries et al., 2018). Among adolescents reporting low levels of upward social comparison, increases in SNS liking were associated with increases in life satisfaction, which corresponds to the emotional contagion perspective (De Vries et al., 2018). However, the individual differences in the associations between SNS liking and life satisfaction were not reduced when upward social comparisons were considered. Also, this was the only moderating effect found out of the six SMU activities that were examined. Therefore, future studies are necessary to replicate our findings.

Our findings provide several implications for future research on the association between SMU intensity and adolescent wellbeing. Specifically, future longitudinal studies that acknowledge heterogeneity in effects, consider SMU problems, and distinguish between within-person and between-person effects would be promising. Research considering these three factors seems more informative than research aiming to disentangle the effects of different SMU activities or examining curvilinear associations. Furthermore, our findings illuminate why earlier studies on the link between SMU intensity and adolescent wellbeing are so inconsistent: Depending on whether researchers investigate specific groups of adolescents, control for SMU problems when examining SMU intensity, or study within-person or between-person associations, the link can range from positive to negative.

In addition, our findings can also inform those concerned with the wellbeing of adolescents, including parents and teachers. They suggest that most adolescents engaging in higher SMU intensity are not at risk for impairments in wellbeing, regardless of whether this concerns engaging in more active or more passive SMU activities. Higher SMU intensity may be considered as normative adolescent behavior that contributes to adolescents' individual development and daily interaction with peers (Granic et al., 2020; Valkenburg & Peter, 2011). Nevertheless, our findings imply that risks to wellbeing could arise when adolescents report SMU problems, indicated by symptoms of addiction (e.g., loss of control over SMU). Therefore, investing in the prevention, early detection, and treatment of problematic SMU may be warranted. Yet, our findings also showed that for a particular group of adolescents, increases in SMU intensity are indicative of decreased wellbeing. Research focusing on identifying the individual characteristics that make adolescents vulnerable to negative SMU effects could provide directions for targeted prevention or intervention programs.

Although we tested many ways in which adolescents' SMU and their wellbeing could be related, the association may be dependent on more factors that were not addressed in this study. First, it may depend on whom adolescents have contact with on social media. For example, longitudinal research on adults showed that receiving Facebook messages from close friends increased wellbeing, whereas receiving such messages from acquaintances did not change wellbeing (Burke & Kraut, 2016). Other research showed that adolescents who reported more Instagram use with close friends reported more friendship closeness than adolescents who showed less Instagram use with close friends (Pouwels et al., 2021). This association was not observed with regards to Instagram use without close friends (Pouwels et al., 2021). Second, the association may depend on the wellbeing outcome being studied. Meta-analytic findings indicate that SMU intensity has different associations with self-esteem and social capital than with life satisfaction (Meier & Reinecke, 2020). Furthermore, research suggests that the association is different for positive indicators of wellbeing than for negative indicators, for example depression and negative affect (Huang, 2017; Wirtz et al., 2020). Third, the association may be contingent on the social media platform used. More specifically, the use of highly visual social media, such as Instagram and Snapchat, may induce more impact than less visual social media, such as Facebook and Twitter. Highly visual social media are mainly focused on uploading visual content, including photos and videos, and allow users to edit this content in more appealing ways using filters (McCrory et al., 2020). Exposure to modified idealized online portrayals may reinforce a negative body image, which, in turn, could undermine wellbeing (Marengo et al., 2018).

## Strengths and Limitations

Using four waves of longitudinal data among secondary school adolescents and a systematic multilevel analytical approach, the present study examined five factors that possibly affect the association between SMU intensity and wellbeing. However, results of this study should be interpreted while considering several limitations. The yearly time intervals of the data used in the present study only allowed for estimating long-term associations. Consequently, potential short-term effects of the intensity of SMU activities could not be captured. Yet, findings from studies on the association between different SMU activities and wellbeing using (multiple) daily assessments showed some comparable results. Often, these studies also observed no average within-person relation between passive and active SMU activities and wellbeing. Also, they showed that these within-person associations ranged from negative to positive across adolescents (Beyens, Pouwels, Valkenburg, et al., 2020; Beyens, Pouwels, Van Driel, et al., 2020; Jensen et al., 2019). Additionally, self-report measures of adolescents' SMU intensity may not accurately represent actual use, because adolescents may over- or underestimate their use. Indeed, research showed a moderate correlation between self-report and tracked SMU (Parry et al., 2020). Research replicating our study using tracked data of SMU activities is warranted. In addition, the present analyses did not explore the direction of the associations between the intensity of SMU activities and life satisfaction. Studying directionality would require a different analytical approach (e.g., random intercept cross-lagged panel modelling), which cannot be adopted within the present multilevel framework. Although we examined life satisfaction as an outcome of higher SMU intensity, a reverse order may be plausible as well. A meta-analysis on the direction of the association supports our assumption, although it investigated the direction of the relation between screen time in general and depression symptoms (Tang et al., 2021). Finally, the data included considerable dropout of adolescents, which may have affected the quality of the data, especially in the final wave. However, this dropout was mostly not due to individual refusal (i.e., not due to selective dropout), but to classes and schools dropping out. Also, we aimed to limit any potential bias by imputing missing data based on available data at all waves (Madley-Dowd et al., 2019).

## Conclusion

Findings from this study showed that at the within-person level, on average, changes in adolescents' intensity of engagement in SMU activities were not associated with changes in their wellbeing (i.e., life satisfaction). However, across adolescents, these within-person associations ranged from negative to positive, suggesting that SMU can be beneficial as well as harmful to wellbeing. At the between-person level, a higher intensity of some SMU activities was associated with lower wellbeing. However, these associations were small and disappeared when controlling for SMU problems. Thus, these negative associations were explained by SMU problems rather than by adolescents' SMU intensity. The results imply that considering individual differences, distinguishing SMU intensity from SMU problems, and disentangling within- from between-person effects are crucial for understanding the association between adolescents' SMU intensity and their wellbeing.

# Appendix

**Table A8.1**

*Fixed Effects Models, Life Satisfaction*

| | m1a | | | | m2a | | | | m1b | | | | m2b | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Level 1 ($n$ = 5,676)** | ***B*** | ***SE*** | ***p*** | ***β*** | ***B*** | ***SE*** | ***p*** | ***β*** | ***B*** | ***SE*** | ***p*** | ***β*** | ***B*** | ***SE*** | ***p*** | ***β*** |
| Wave | -0.149 | 0.015 | <0.001 | -0.254 | -0.152 | 0.018 | <0.001 | -0.259 | -0.152 | 0.014 | <0.001 | -0.259 | -0.150 | 0.015 | <0.001 | -0.256 |
| SMU problems | | | | | -0.106 | 0.011 | <0.001 | -0.168 | | | | | -0.104 | 0.010 | <0.001 | -0.164 |
| SNS viewing | -0.003 | 0.011 | 0.807 | -0.005 | 0.012 | 0.013 | 0.356 | 0.020 | | | | | | | | |
| SNS posting | | | | | | | | | -0.012 | 0.008 | 0.136 | -0.021 | -0.008 | 0.009 | 0.356 | -0.014 |
| SNS liking | | | | | | | | | | | | | | | | |
| SNS responding | | | | | | | | | | | | | | | | |
| IM viewing | | | | | | | | | | | | | | | | |
| IM sending | | | | | | | | | | | | | | | | |
| **Level 2 ($n$ = 1,419)** | ***B*** | ***SE*** | ***p*** | ***β*** | ***B*** | ***SE*** | ***p*** | ***β*** | ***B*** | ***SE*** | ***p*** | ***β*** | ***B*** | ***SE*** | ***p*** | ***β*** |
| Female | -0.093 | 0.038 | 0.014 | -0.177 | -0.086 | 0.034 | 0.011 | -0.162 | -0.106 | 0.035 | 0.002 | -0.202 | -0.078 | 0.032 | 0.016 | -0.147 |
| Pre-vocational education | 0.001 | 0.041 | 0.981 | 0.002 | 0.046 | 0.041 | 0.266 | 0.087 | -0.001 | 0.037 | 0.971 | -0.002 | 0.049 | 0.040 | 0.223 | 0.092 |
| Immigrant background | 0.020 | 0.059 | 0.732 | 0.039 | 0.020 | 0.058 | 0.735 | 0.038 | 0.021 | 0.059 | 0.721 | 0.040 | 0.019 | 0.058 | 0.741 | 0.037 |
| SMU problems | | | | | -0.197 | 0.018 | <0.001 | -0.412 | | | | | -0.193 | 0.018 | <0.001 | -0.403 |
| SNS viewing | -0.036 | 0.018 | 0.048 | -0.084 | 0.022 | 0.017 | 0.192 | 0.051 | | | | | | | | |
| SNS posting | | | | | | | | | -0.040 | 0.026 | 0.127 | -0.069 | 0.017 | 0.029 | 0.554 | 0.029 |
| SNS liking | | | | | | | | | | | | | | | | |
| SNS responding | | | | | | | | | | | | | | | | |
| IM viewing | | | | | | | | | | | | | | | | |
| IM sending | | | | | | | | | | | | | | | | |
| **Random parameters** | **Est.** | ***SE*** | ***p*** | | **Est.** | ***SE*** | ***p*** | | **Est.** | ***SE*** | ***p*** | | **Est.** | ***SE*** | ***p*** | |
| Residual variance within | 0.404 | 0.013 | <0.001 | | 0.388 | 0.014 | <0.001 | | 0.404 | 0.013 | <0.001 | | 0.388 | 0.013 | <0.001 | |
| Residual variance between | 0.272 | 0.017 | <0.001 | | 0.234 | 0.015 | <0.001 | | 0.272 | 0.016 | <0.001 | | 0.235 | 0.015 | <0.001 | |
| **Explained variance** | **Est.** | | | | **Est.** | | | | **Est.** | | | | **Est.** | | | |
| $R^2$ within | 0.066 | | | | 0.094 | | | | 0.066 | | | | 0.093 | | | |
| $R^2$ between | 0.019 | | | | 0.165 | | | | 0.017 | | | | 0.165 | | | |
| **Fit statistics** | **Par.** | **Deviance** | **AIC** | **BIC** | **Par.** | **Deviance** | **AIC** | **BIC** | **Par.** | **Deviance** | **AIC** | **BIC** | **Par.** | **Deviance** | **AIC** | **BIC** |
| Model fit | 9 | 12814.7 | 12832.7 | 12892.5 | 11 | 12478.5 | 12500.5 | 12573.6 | 9 | 12814.9 | 12832.9 | 12892.7 | 11 | 12481.7 | 12503.7 | 12576.8 |

*Notes.* SNS = social network sites; IM = instant messengers; SMU = social media use; Level 1 = yearly measurements; Level 2 = adolescents; *B* = unstandardized coefficient; *SE* = standard error, *p* = *p*-value; *β* = STDY-standardized for dichotomous variables (female, prevocational education, and immigrant background) and STDYX-standardized for the other variables; Est. = estimate; Par. = number of free parameters; Deviance = -2*loglikelihood; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion.

**Table A8.1 (continued)**

*Fixed Effects Models, Life Satisfaction*

| | m1c | | | | m2c | | | | m1d | | | | m2d | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Level 1 (*n* = 5,676)** | ***B*** | ***SE*** | ***p*** | ***β*** | ***B*** | ***SE*** | ***p*** | ***β*** | ***B*** | ***SE*** | ***p*** | ***β*** | ***B*** | ***SE*** | ***p*** | ***β*** |
| Wave | -0.149 | 0.014 | <0.001 | -0.254 | -0.149 | 0.015 | <0.001 | -0.254 | -0.148 | 0.015 | <0.001 | -0.251 | -0.147 | 0.016 | <0.001 | -0.251 |
| SMU problems | | | | | -0.104 | 0.010 | <0.001 | -0.165 | | | | | -0.102 | 0.010 | <0.001 | -0.162 |
| SNS viewing | | | | | | | | | | | | | | | | |
| SNS posting | | | | | | | | | | | | | | | | |
| SNS liking | -0.005 | 0.007 | 0.499 | -0.010 | 0.003 | 0.007 | 0.658 | 0.006 | | | | | | | | |
| SNS responding | | | | | | | | | -0.022 | 0.012 | 0.062 | -0.044 | -0.011 | 0.013 | 0.364 | -0.023 |
| IM viewing | | | | | | | | | | | | | | | | |
| IM sending | | | | | | | | | | | | | | | | |
| **Level 2 (*n* = 1,419)** | ***B*** | ***SE*** | ***p*** | ***β*** | ***B*** | ***SE*** | ***p*** | ***β*** | ***B*** | ***SE*** | ***p*** | ***β*** | ***B*** | ***SE*** | ***p*** | ***β*** |
| Female | -0.098 | 0.037 | 0.008 | -0.186 | -0.088 | 0.034 | 0.009 | -0.166 | -0.096 | 0.040 | 0.018 | -0.182 | -0.101 | 0.037 | 0.006 | -0.191 |
| Pre-vocational education | -0.016 | 0.041 | 0.693 | -0.030 | 0.053 | 0.042 | 0.208 | 0.101 | -0.012 | 0.041 | 0.769 | -0.023 | 0.042 | 0.042 | 0.323 | 0.080 |
| Immigrant background | 0.014 | 0.059 | 0.808 | 0.028 | 0.025 | 0.059 | 0.667 | 0.048 | 0.018 | 0.059 | 0.764 | 0.034 | 0.023 | 0.059 | 0.691 | 0.045 |
| SMU problems | | | | | -0.195 | 0.019 | <0.001 | -0.407 | | | | | -0.198 | 0.017 | <0.001 | -0.412 |
| SNS viewing | | | | | | | | | | | | | | | | |
| SNS posting | | | | | | | | | | | | | | | | |
| SNS liking | -0.015 | 0.013 | 0.258 | -0.044 | 0.016 | 0.014 | 0.238 | 0.048 | | | | | | | | |
| SNS responding | | | | | | | | | -0.013 | 0.016 | 0.420 | -0.035 | 0.027 | 0.016 | 0.080 | 0.072 |
| IM viewing | | | | | | | | | | | | | | | | |
| IM sending | | | | | | | | | | | | | | | | |
| **Random parameters** | **Est.** | ***SE*** | ***p*** | | **Est.** | ***SE*** | ***p*** | | **Est.** | ***SE*** | ***p*** | | **Est.** | ***SE*** | ***p*** | |
| Residual variance within | 0.404 | 0.013 | <0.001 | | 0.388 | 0.013 | <0.001 | | 0.403 | 0.013 | <0.001 | | 0.388 | 0.013 | <0.001 | |
| Residual variance between | 0.273 | 0.017 | <0.001 | | 0.234 | 0.015 | <0.001 | | 0.273 | 0.017 | <0.001 | | 0.234 | 0.015 | <0.001 | |
| **Explained variance** | **Est.** | | | | **Est.** | | | | **Est.** | | | | **Est.** | | | |
| $R^2$ within | 0.066 | | | | 0.093 | | | | 0.068 | | | | 0.094 | | | |
| $R^2$ between | 0.014 | | | | 0.165 | | | | 0.013 | | | | 0.167 | | | |
| **Fit statistics** | **Par.** | **Deviance** | **AIC** | **BIC** | **Par.** | **Deviance** | **AIC** | **BIC** | **Par.** | **Deviance** | **AIC** | **BIC** | **Par.** | **Deviance** | **AIC** | **BIC** |
| Model fit | 9 | 12820.0 | 12838.0 | 12897.8 | 11 | 12481.6 | 12503.6 | 12576.7 | 9 | 12808.4 | 12826.4 | 12886.2 | 11 | 12474.3 | 12496.3 | 12569.4 |

*Notes.* SNS = social network sites; IM = instant messengers; SMU = social media use; Level 1 = yearly measurements; Level 2 = adolescents; *B* = unstandardized coefficient; *SE* = standard error, *p* = *p*-value; ***β*** = STDY-standardized for dichotomous variables (female, prevocational education, and immigrant background) and STDYX-standardized for the other variables; Est. = estimate; Par. = number of free parameters; Deviance = -2*loglikelihood; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion.

8

**Table A8.1 (continued)**

*Fixed Effects Models, Life Satisfaction*

| | m1e | | | | m2e | | | | m1f | | | | m2f | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Level 1 ($n$ = 5,676)** | ***B*** | ***SE*** | ***p*** | ***β*** | ***B*** | ***SE*** | ***p*** | ***β*** | ***B*** | ***SE*** | ***p*** | ***β*** | ***B*** | ***SE*** | ***p*** | ***β*** |
| Wave | -0.148 | 0.014 | <0.001 | -0.252 | -0.149 | 0.015 | <0.001 | -0.255 | -0.149 | 0.014 | <0.001 | -0.253 | -0.148 | 0.015 | <0.001 | -0.253 |
| SMU problems | | | | | -0.105 | 0.010 | <0.001 | -0.167 | | | | | -0.102 | 0.009 | <0.001 | -0.162 |
| SNS viewing | | | | | | | | | | | | | | | | |
| SNS posting | | | | | | | | | | | | | | | | |
| SNS liking | | | | | | | | | | | | | | | | |
| SNS responding | | | | | | | | | | | | | | | | |
| IM viewing | -0.013 | 0.011 | 0.247 | -0.021 | 0.007 | 0.011 | 0.552 | 0.011 | | | | | | | | |
| IM sending | | | | | | | | | -0.025 | 0.012 | 0.046 | -0.043 | -0.011 | 0.013 | 0.385 | -0.019 |
| **Level 2 ($n$ = 1,419)** | ***B*** | ***SE*** | ***p*** | ***β*** | ***B*** | ***SE*** | ***p*** | ***β*** | ***B*** | ***SE*** | ***p*** | ***β*** | ***B*** | ***SE*** | ***p*** | ***β*** |
| Female | -0.095 | 0.036 | 0.007 | -0.181 | -0.081 | 0.032 | 0.012 | -0.154 | -0.095 | 0.035 | 0.007 | -0.180 | -0.082 | 0.033 | 0.012 | -0.155 |
| Pre-vocational education | -0.002 | 0.041 | 0.956 | -0.004 | 0.051 | 0.042 | 0.222 | 0.098 | -0.010 | 0.040 | 0.813 | -0.018 | 0.053 | 0.042 | 0.203 | 0.101 |
| Immigrant background | 0.008 | 0.059 | 0.892 | 0.016 | 0.024 | 0.059 | 0.681 | 0.046 | 0.009 | 0.059 | 0.874 | 0.018 | 0.023 | 0.058 | 0.689 | 0.044 |
| SMU problems | | | | | -0.196 | 0.020 | <0.001 | -0.409 | | | | | -0.194 | 0.019 | <0.001 | -0.404 |
| SNS viewing | | | | | | | | | | | | | | | | |
| SNS posting | | | | | | | | | | | | | | | | |
| SNS liking | | | | | | | | | | | | | | | | |
| SNS responding | | | | | | | | | | | | | | | | |
| IM viewing | -0.046 | 0.015 | 0.002 | -0.106 | 0.016 | 0.016 | 0.299 | 0.037 | | | | | | | | |
| IM sending | | | | | | | | | -0.036 | 0.013 | 0.008 | -0.087 | 0.012 | 0.014 | 0.409 | 0.029 |
| **Random parameters** | **Est.** | ***SE*** | ***p*** | | **Est.** | ***SE*** | ***p*** | | **Est.** | ***SE*** | ***p*** | | **Est.** | ***SE*** | ***p*** | |
| Residual variance within | 0.404 | 0.014 | <0.001 | | 0.388 | 0.013 | <0.001 | | 0.403 | 0.013 | <0.001 | | 0.388 | 0.013 | <0.001 | |
| Residual variance between | 0.271 | 0.017 | <0.001 | | 0.235 | 0.015 | <0.001 | | 0.272 | 0.017 | <0.001 | | 0.235 | 0.015 | <0.001 | |
| **Explained variance** | **Est.** | | | | **Est.** | | | | **Est.** | | | | **Est.** | | | |
| $R^2$ within | 0.066 | | | | 0.093 | | | | 0.068 | | | | 0.094 | | | |
| $R^2$ between | 0.023 | | | | 0.164 | | | | 0.019 | | | | 0.164 | | | |
| **Fit statistics** | **Par.** | **Deviance** | **AIC** | **BIC** | **Par.** | **Deviance** | **AIC** | **BIC** | **Par.** | **Deviance** | **AIC** | **BIC** | **Par.** | **Deviance** | **AIC** | **BIC** |
| Model fit | 9 | 12808.4 | 12826.4 | 12886.2 | 11 | 12482.2 | 12504.2 | 12577.3 | 9 | 12802.6 | 12820.6 | 12880.4 | 11 | 12480.3 | 12502.3 | 12575.4 |

*Notes.* SNS = social network sites; IM = instant messengers; SMU = social media use; Level 1 = yearly measurements; Level 2 = adolescents; $B$ = unstandardized coefficient; $SE$ = standard error, $p$ = $p$-value; $\beta$ = STDY-standardized for dichotomous variables (female, prevocational education, and immigrant background) and STDYX-standardized for the other variables; Est. = estimate; Par. = number of free parameters; Deviance = -2*loglikelihood; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion.

**Table A8.1 (continued)**

*Fixed Effects Models, Life Satisfaction*

| | **mX** | | | |
|---|---|---|---|---|
| **Level 1 (*n* = 5,676)** | ***B*** | ***SE*** | ***p*** | ***β*** |
| Wave | -0.156 | 0.018 | <0.001 | -0.266 |
| SMU problems | -0.104 | 0.010 | <0.001 | -0.165 |
| SNS viewing | 0.019 | 0.015 | 0.220 | 0.032 |
| SNS posting | -0.007 | 0.008 | 0.398 | -0.012 |
| SNS liking | 0.006 | 0.009 | 0.512 | 0.012 |
| SNS responding | -0.017 | 0.015 | 0.249 | -0.035 |
| IM viewing | 0.014 | 0.014 | 0.313 | 0.022 |
| IM sending | -0.018 | 0.014 | 0.192 | -0.032 |
| **Level 2 (*n* = 1,419)** | ***B*** | ***SE*** | ***p*** | ***β*** |
| Female | -0.100 | 0.039 | 0.010 | -0.188 |
| Pre-vocational education | 0.040 | 0.042 | 0.334 | 0.076 |
| Immigrant background | 0.021 | 0.057 | 0.708 | 0.040 |
| SMU problems | -0.198 | 0.019 | <0.001 | -0.414 |
| SNS viewing | 0.007 | 0.029 | 0.805 | 0.017 |
| SNS posting | 0.003 | 0.034 | 0.940 | 0.004 |
| SNS liking | 0.002 | 0.022 | 0.922 | 0.006 |
| SNS responding | 0.025 | 0.028 | 0.385 | 0.065 |
| IM viewing | 0.001 | 0.029 | 0.985 | 0.001 |
| IM sending | -0.008 | 0.022 | 0.708 | -0.020 |
| **Random parameters** | **Est.** | ***SE*** | ***p*** | |
| Residual variance within | 0.387 | 0.013 | <0.001 | |
| Residual variance between | 0.233 | 0.015 | <0.001 | |
| **Explained variance** | **Est.** | | | |
| $R^2$ within | 0.097 | | | |
| $R^2$ between | 0.170 | | | |
| **Fit statistics** | **Par.** | **Deviance** | **AIC** | **BIC** |
| Model fit | 21 | 12455.5 | 12497.5 | 12637.0 |

*Notes.* SNS = social network sites; IM = instant messengers; SMU = social media use; Level 1 = yearly measurements; Level 2 = adolescents; *B* = unstandardized coefficient; *SE* = standard error, *p* = *p*-value; ***β*** = STDY-standardized for dichotomous variables (female, prevocational education, and immigrant background) and STDYX-standardized for the other variables; Est. = estimate; Par. = number of free parameters; Deviance = -2*loglikelihood; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion.

8

**Table A8.2**

*Fixed Effects Models with Quadratic Effects, Life Satisfaction*

| | m3a | | | | m4a | | | |
|---|---|---|---|---|---|---|---|---|
| **Level 1 (*n* = 5,676)** | ***B*** | ***SE*** | ***p*** | ***β*** | ***B*** | ***SE*** | ***p*** | ***β*** |
| Wave | -0.149 | 0.015 | <0.001 | -0.253 | -0.151 | 0.018 | <0.001 | -0.259 |
| SMU problems | | | | | -0.106 | 0.011 | <0.001 | -0.167 |
| SNS viewing | -0.002 | 0.011 | 0.849 | -0.004 | 0.012 | 0.013 | 0.334 | 0.021 |
| SNS viewing$^{\wedge 2}$ | 0.010 | 0.008 | 0.209 | 0.028 | 0.010 | 0.007 | 0.188 | 0.027 |
| SNS posting | | | | | | | | |
| SNS posting$^{\wedge 2}$ | | | | | | | | |
| SNS liking | | | | | | | | |
| SNS liking$^{\wedge 2}$ | | | | | | | | |
| SNS responding | | | | | | | | |
| SNS responding$^{\wedge 2}$ | | | | | | | | |
| IM viewing | | | | | | | | |
| IM viewing$^{\wedge 2}$ | | | | | | | | |
| IM sending | | | | | | | | |
| IM sending$^{\wedge 2}$ | | | | | | | | |
| **Level 2 (*n* = 1,419)** | ***B*** | ***SE*** | ***p*** | ***β*** | ***B*** | ***SE*** | ***p*** | ***β*** |
| Female | -0.093 | 0.038 | 0.013 | -0.177 | -0.085 | 0.034 | 0.012 | -0.161 |
| Pre-vocational education | -0.001 | 0.041 | 0.986 | -0.001 | 0.044 | 0.041 | 0.283 | 0.084 |
| Immigrant background | 0.022 | 0.059 | 0.711 | 0.042 | 0.021 | 0.058 | 0.725 | 0.039 |
| SMU problems | | | | | -0.197 | 0.018 | <0.001 | -0.411 |
| SNS viewing | -0.038 | 0.019 | 0.042 | -0.089 | 0.021 | 0.017 | 0.222 | 0.049 |
| SNS viewing$^{\wedge 2}$ | -0.010 | 0.011 | 0.381 | -0.035 | -0.003 | 0.009 | 0.704 | -0.012 |
| SNS posting | | | | | | | | |
| SNS posting$^{\wedge 2}$ | | | | | | | | |
| SNS liking | | | | | | | | |
| SNS liking$^{\wedge 2}$ | | | | | | | | |
| SNS responding | | | | | | | | |
| SNS responding$^{\wedge 2}$ | | | | | | | | |
| IM viewing | | | | | | | | |
| IM viewing$^{\wedge 2}$ | | | | | | | | |
| IM sending | | | | | | | | |
| IM sending$^{\wedge 2}$ | | | | | | | | |
| **Random parameters** | **Est.** | ***SE*** | ***p*** | | **Est.** | ***SE*** | ***p*** | |
| Residual variance within | 0.403 | 0.013 | <0.001 | | 0.388 | 0.013 | <0.001 | |
| Residual variance between | 0.272 | 0.017 | <0.001 | | 0.235 | 0.015 | <0.001 | |
| **Explained variance** | **Est.** | | | | **Est.** | | | |
| $R^2$ within | 0.067 | | | | 0.095 | | | |
| $R^2$ between | 0.020 | | | | 0.165 | | | |
| **Fit statistics** | **Par.** | **Deviance** | **AIC** | **BIC** | **Par.** | **Deviance** | **AIC** | **BIC** |
| Model fit | 11 | 12808.3 | 12830.3 | 12903.3 | 13 | 12474.1 | 12500.1 | 12586.4 |

*Notes.* SNS = social network sites; IM = instant messengers; SMU = social media use; Level 1 = yearly measurements; Level 2 = adolescents; *B* = unstandardized coefficient; *SE* = standard error, *p* = *p*-value; ***β*** = STDY-standardized for dichotomous variables (female, prevocational education, and immigrant background) and STDYX-standardized for the other variables; Est. = estimate; Par. = number of free parameters; Deviance = -2*loglikelihood; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion.

**Table A8.2 (continued)**

*Fixed Effects Models with Quadratic Effects, Life Satisfaction*

| | m3b | | | | m4b | | | |
|---|---|---|---|---|---|---|---|---|
| **Level 1 (*n* = 5,676)** | ***B*** | ***SE*** | ***p*** | ***β*** | ***B*** | ***SE*** | ***p*** | ***β*** |
| Wave | -0.154 | 0.013 | <0.001 | -0.261 | -0.151 | 0.014 | <0.001 | -0.258 |
| SMU problems | | | | | -0.104 | 0.010 | <0.001 | -0.164 |
| SNS viewing | | | | | | | | |
| SNS viewing^2 | | | | | | | | |
| SNS posting | -0.022 | 0.011 | 0.050 | -0.038 | -0.016 | 0.012 | 0.177 | -0.028 |
| SNS posting^2 | 0.010 | 0.007 | 0.140 | 0.040 | 0.009 | 0.007 | 0.238 | 0.034 |
| SNS liking | | | | | | | | |
| SNS liking^2 | | | | | | | | |
| SNS responding | | | | | | | | |
| SNS responding^2 | | | | | | | | |
| IM viewing | | | | | | | | |
| IM viewing^2 | | | | | | | | |
| IM sending | | | | | | | | |
| IM sending^2 | | | | | | | | |
| **Level 2 (*n* = 1,419)** | ***B*** | ***SE*** | ***p*** | ***β*** | ***B*** | ***SE*** | ***p*** | ***β*** |
| Female | -0.099 | 0.036 | 0.006 | -0.188 | -0.075 | 0.033 | 0.024 | -0.141 |
| Pre-vocational education | 0.004 | 0.037 | 0.909 | 0.008 | 0.050 | 0.039 | 0.197 | 0.095 |
| Immigrant background | 0.020 | 0.058 | 0.727 | 0.039 | 0.019 | 0.058 | 0.746 | 0.036 |
| SMU problems | | | | | -0.192 | 0.018 | <0.001 | -0.401 |
| SNS viewing | | | | | | | | |
| SNS viewing^2 | | | | | | | | |
| SNS posting | -0.079 | 0.032 | 0.014 | -0.137 | -0.001 | 0.033 | 0.972 | -0.003 |
| SNS posting^2 | 0.021 | 0.019 | 0.268 | 0.063 | 0.006 | 0.018 | 0.750 | 0.017 |
| SNS liking | | | | | | | | |
| SNS liking^2 | | | | | | | | |
| SNS responding | | | | | | | | |
| SNS responding^2 | | | | | | | | |
| IM viewing | | | | | | | | |
| IM viewing^2 | | | | | | | | |
| IM sending | | | | | | | | |
| IM sending^2 | | | | | | | | |
| **Random parameters** | **Est.** | ***SE*** | ***p*** | | **Est.** | ***SE*** | ***p*** | |
| Residual variance within | 0.403 | 0.013 | <0.001 | | 0.388 | 0.013 | <0.001 | |
| Residual variance between | 0.271 | 0.016 | <0.001 | | 0.234 | 0.015 | <0.001 | |
| **Explained variance** | **Est.** | | | | **Est.** | | | |
| $R^2$ within | 0.067 | | | | 0.095 | | | |
| $R^2$ between | 0.022 | | | | 0.167 | | | |
| **Fit statistics** | **Par.** | **Deviance** | **AIC** | **BIC** | **Par.** | **Deviance** | **AIC** | **BIC** |
| Model fit | 11 | 12807.7 | 12829.7 | 12902.8 | 13 | 12477.0 | 12503.0 | 12589.4 |

*Notes.* SNS = social network sites; IM = instant messengers; SMU = social media use; Level 1 = yearly measurements; Level 2 = adolescents; *B* = unstandardized coefficient; *SE* = standard error, *p* = *p*-value; ***β*** = STDY-standardized for dichotomous variables (female, prevocational education, and immigrant background) and STDYX-standardized for the other variables; Est. = estimate; Par. = number of free parameters; Deviance = -2*loglikelihood; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion.

**Table A8.2 (continued)**

*Fixed Effects Models with Quadratic Effects, Life Satisfaction*

| | m3c | | | | m4c | | | |
|---|---|---|---|---|---|---|---|---|
| **Level 1 (*n* = 5,676)** | ***B*** | ***SE*** | ***p*** | ***β*** | ***B*** | ***SE*** | ***p*** | ***β*** |
| Wave | -0.149 | 0.014 | <0.001 | -0.253 | -0.149 | 0.016 | <0.001 | -0.254 |
| SMU problems | | | | | -0.104 | 0.010 | <0.001 | -0.166 |
| SNS viewing | | | | | | | | |
| SNS viewing^2 | | | | | | | | |
| SNS posting | | | | | | | | |
| SNS posting^2 | | | | | | | | |
| SNS liking | -0.004 | 0.007 | 0.574 | -0.008 | 0.004 | 0.007 | 0.588 | 0.008 |
| SNS liking^2 | 0.002 | 0.005 | 0.755 | 0.007 | 0.002 | 0.005 | 0.693 | 0.008 |
| SNS responding | | | | | | | | |
| SNS responding^2 | | | | | | | | |
| IM viewing | | | | | | | | |
| IM viewing^2 | | | | | | | | |
| IM sending | | | | | | | | |
| IM sending^2 | | | | | | | | |
| **Level 2 (*n* = 1,419)** | ***B*** | ***SE*** | ***p*** | ***β*** | ***B*** | ***SE*** | ***p*** | ***β*** |
| Female | -0.097 | 0.037 | 0.008 | -0.185 | -0.087 | 0.034 | 0.010 | -0.164 |
| Pre-vocational education | -0.016 | 0.041 | 0.692 | -0.030 | 0.053 | 0.042 | 0.210 | 0.101 |
| Immigrant background | 0.014 | 0.059 | 0.811 | 0.027 | 0.025 | 0.059 | 0.668 | 0.048 |
| SMU problems | | | | | -0.195 | 0.019 | <0.001 | -0.407 |
| SNS viewing | | | | | | | | |
| SNS viewing^2 | | | | | | | | |
| SNS posting | | | | | | | | |
| SNS posting^2 | | | | | | | | |
| SNS liking | -0.014 | 0.015 | 0.357 | -0.042 | 0.018 | 0.015 | 0.226 | 0.053 |
| SNS liking^2 | <0.001 | 0.007 | 0.976 | 0.001 | 0.001 | 0.006 | 0.859 | 0.007 |
| SNS responding | | | | | | | | |
| SNS responding^2 | | | | | | | | |
| IM viewing | | | | | | | | |
| IM viewing^2 | | | | | | | | |
| IM sending | | | | | | | | |
| IM sending^2 | | | | | | | | |
| **Random parameters** | **Est.** | ***SE*** | ***p*** | | **Est.** | ***SE*** | ***p*** | |
| Residual variance within | 0.404 | 0.013 | <0.001 | | 0.388 | 0.013 | <0.001 | |
| Residual variance between | 0.273 | 0.017 | <0.001 | | 0.235 | 0.015 | <0.001 | |
| **Explained variance** | **Est.** | | | | **Est.** | | | |
| $R^2$ within | 0.066 | | | | 0.094 | | | |
| $R^2$ between | 0.014 | | | | 0.165 | | | |
| **Fit statistics** | **Par.** | **Deviance** | **AIC** | **BIC** | **Par.** | **Deviance** | **AIC** | **BIC** |
| Model fit | 11 | 12819.0 | 12841.0 | 12914.1 | 13 | 12480.7 | 12506.7 | 12593.0 |

*Notes.* SNS = social network sites; IM = instant messengers; SMU = social media use; Level 1 = yearly measurements; Level 2 = adolescents; *B* = unstandardized coefficient; *SE* = standard error, *p* = *p*-value; **β** = STDY-standardized for dichotomous variables (female, prevocational education, and immigrant background) and STDYX-standardized for the other variables; Est. = estimate; Par. = number of free parameters; Deviance = -2*loglikelihood; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion.

**Table A8.2 (continued)**

*Fixed Effects Models with Quadratic Effects, Life Satisfaction*

| | m3d | | | | m4d | | | |
|---|---|---|---|---|---|---|---|---|
| **Level 1 ($n$ = 5,676)** | ***B*** | ***SE*** | ***p*** | ***β*** | ***B*** | ***SE*** | ***p*** | ***β*** |
| Wave | -0.148 | 0.015 | <0.001 | -0.252 | -0.147 | 0.016 | <0.001 | -0.251 |
| SMU problems | | | | | -0.102 | 0.010 | <0.001 | -0.162 |
| SNS viewing | | | | | | | | |
| SNS viewing^2 | | | | | | | | |
| SNS posting | | | | | | | | |
| SNS posting^2 | | | | | | | | |
| SNS liking | | | | | | | | |
| SNS liking^2 | | | | | | | | |
| SNS responding | -0.022 | 0.012 | 0.062 | -0.045 | -0.012 | 0.013 | 0.352 | -0.025 |
| SNS responding^2 | 0.008 | 0.006 | 0.201 | 0.030 | 0.008 | 0.005 | 0.159 | 0.029 |
| IM viewing | | | | | | | | |
| IM viewing^2 | | | | | | | | |
| IM sending | | | | | | | | |
| IM sending^2 | | | | | | | | |
| **Level 2 ($n$ = 1,419)** | ***B*** | ***SE*** | ***p*** | ***β*** | ***B*** | ***SE*** | ***p*** | ***β*** |
| Female | -0.095 | 0.041 | 0.020 | -0.181 | -0.101 | 0.037 | 0.006 | -0.191 |
| Pre-vocational education | -0.014 | 0.041 | 0.732 | -0.026 | 0.039 | 0.042 | 0.350 | 0.074 |
| Immigrant background | 0.018 | 0.059 | 0.763 | 0.034 | 0.023 | 0.059 | 0.693 | 0.044 |
| SMU problems | | | | | -0.199 | 0.018 | <0.001 | -0.415 |
| SNS viewing | | | | | | | | |
| SNS viewing^2 | | | | | | | | |
| SNS posting | | | | | | | | |
| SNS posting^2 | | | | | | | | |
| SNS liking | | | | | | | | |
| SNS liking^2 | | | | | | | | |
| SNS responding | -0.015 | 0.017 | 0.384 | -0.038 | 0.027 | 0.016 | 0.088 | 0.072 |
| SNS responding^2 | -0.003 | 0.008 | 0.693 | -0.013 | -0.008 | 0.009 | 0.384 | -0.031 |
| IM viewing | | | | | | | | |
| IM viewing^2 | | | | | | | | |
| IM sending | | | | | | | | |
| IM sending^2 | | | | | | | | |
| **Random parameters** | **Est.** | ***SE*** | ***p*** | | **Est.** | ***SE*** | ***p*** | |
| Residual variance within | 0.402 | 0.012 | <0.001 | | 0.388 | 0.013 | <0.001 | |
| Residual variance between | 0.274 | 0.017 | <0.001 | | 0.234 | 0.015 | <0.001 | |
| **Explained variance** | **Est.** | | | | **Est.** | | | |
| $R^2$ within | 0.069 | | | | 0.095 | | | |
| $R^2$ between | 0.014 | | | | 0.170 | | | |
| **Fit statistics** | **Par.** | **Deviance** | **AIC** | **BIC** | **Par.** | **Deviance** | **AIC** | **BIC** |
| Model fit | 11 | 12803.0 | 12825.0 | 12898.0 | 13 | 12467.7 | 12493.7 | 12580.1 |

*Notes.* SNS = social network sites; IM = instant messengers; SMU = social media use; Level 1 = yearly measurements; Level 2 = adolescents; $B$ = unstandardized coefficient; $SE$ = standard error, $p$ = $p$-value; **β** = STDY-standardized for dichotomous variables (female, prevocational education, and immigrant background) and STDYX-standardized for the other variables; Est. = estimate; Par. = number of free parameters; Deviance = -2*loglikelihood; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion.

**Table A8.2 (continued)**

*Fixed Effects Models with Quadratic Effects, Life Satisfaction*

| | m3e | | | | m4e | | | |
|---|---|---|---|---|---|---|---|---|
| **Level 1 (*n* = 5,676)** | ***B*** | ***SE*** | ***p*** | ***β*** | ***B*** | ***SE*** | ***p*** | ***β*** |
| Wave | -0.149 | 0.014 | <0.001 | -0.253 | -0.150 | 0.015 | <0.001 | -0.256 |
| SMU problems | | | | | -0.105 | 0.010 | <0.001 | -0.167 |
| SNS viewing | | | | | | | | |
| SNS viewing^2 | | | | | | | | |
| SNS posting | | | | | | | | |
| SNS posting^2 | | | | | | | | |
| SNS liking | | | | | | | | |
| SNS liking^2 | | | | | | | | |
| SNS responding | | | | | | | | |
| SNS responding^2 | | | | | | | | |
| IM viewing | -0.014 | 0.012 | 0.231 | -0.021 | 0.006 | 0.012 | 0.584 | 0.010 |
| IM viewing^2 | -0.009 | 0.007 | 0.205 | -0.021 | -0.006 | 0.007 | 0.393 | -0.014 |
| IM sending | | | | | | | | |
| IM sending^2 | | | | | | | | |
| **Level 2 (*n* = 1,419)** | ***B*** | ***SE*** | ***p*** | ***β*** | ***B*** | ***SE*** | ***p*** | ***β*** |
| Female | -0.096 | 0.036 | 0.008 | -0.183 | -0.080 | 0.033 | 0.016 | -0.151 |
| Pre-vocational education | -0.001 | 0.041 | 0.974 | -0.002 | 0.051 | 0.042 | 0.227 | 0.097 |
| Immigrant background | 0.008 | 0.060 | 0.897 | 0.015 | 0.022 | 0.060 | 0.710 | 0.043 |
| SMU problems | | | | | -0.196 | 0.020 | <0.001 | -0.410 |
| SNS viewing | | | | | | | | |
| SNS viewing^2 | | | | | | | | |
| SNS posting | | | | | | | | |
| SNS posting^2 | | | | | | | | |
| SNS liking | | | | | | | | |
| SNS liking^2 | | | | | | | | |
| SNS responding | | | | | | | | |
| SNS responding^2 | | | | | | | | |
| IM viewing | -0.047 | 0.015 | 0.002 | -0.107 | 0.018 | 0.016 | 0.261 | 0.042 |
| IM viewing^2 | <0.001 | 0.012 | 0.996 | <0.001 | 0.007 | 0.013 | 0.575 | 0.024 |
| IM sending | | | | | | | | |
| IM sending^2 | | | | | | | | |
| **Random parameters** | **Est.** | ***SE*** | ***p*** | | **Est.** | ***SE*** | ***p*** | |
| Residual variance within | 0.404 | 0.014 | <0.001 | | 0.388 | 0.013 | <0.001 | |
| Residual variance between | 0.270 | 0.017 | <0.001 | | 0.234 | 0.014 | <0.001 | |
| **Explained variance** | **Est.** | | | | **Est.** | | | |
| $R^2$ within | 0.066 | | | | 0.094 | | | |
| $R^2$ between | 0.023 | | | | 0.165 | | | |
| **Fit statistics** | **Par.** | **Deviance** | **AIC** | **BIC** | **Par.** | **Deviance** | **AIC** | **BIC** |
| Model fit | 11 | 12806.0 | 12828.0 | 12901.0 | 13 | 12479.6 | 12505.6 | 12591.9 |

*Notes.* SNS = social network sites; IM = instant messengers; SMU = social media use; Level 1 = yearly measurements; Level 2 = adolescents; *B* = unstandardized coefficient; *SE* = standard error, *p* = *p*-value; ***β*** = STDY-standardized for dichotomous variables (female, prevocational education, and immigrant background) and STDYX-standardized for the other variables; Est. = estimate; Par. = number of free parameters; Deviance = -2*loglikelihood; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion.

**Table A8.2 (continued)**

*Fixed Effects Models with Quadratic Effects, Life Satisfaction*

| | m3f | | | | m4f | | | |
|---|---|---|---|---|---|---|---|---|
| **Level 1 (*n* = 5,676)** | ***B*** | ***SE*** | ***p*** | ***β*** | ***B*** | ***SE*** | ***p*** | ***β*** |
| Wave | -0.149 | 0.014 | <0.001 | -0.253 | -0.148 | 0.015 | <0.001 | -0.252 |
| SMU problems | | | | | -0.102 | 0.009 | <0.001 | -0.162 |
| SNS viewing | | | | | | | | |
| SNS viewing^2 | | | | | | | | |
| SNS posting | | | | | | | | |
| SNS posting^2 | | | | | | | | |
| SNS liking | | | | | | | | |
| SNS liking^2 | | | | | | | | |
| SNS responding | | | | | | | | |
| SNS responding^2 | | | | | | | | |
| IM viewing | | | | | | | | |
| IM viewing^2 | | | | | | | | |
| IM sending | -0.024 | 0.012 | 0.049 | -0.043 | -0.010 | 0.013 | 0.408 | -0.018 |
| IM sending^2 | 0.005 | 0.009 | 0.608 | 0.014 | 0.006 | 0.009 | 0.481 | 0.020 |
| **Level 2 (*n* = 1,419)** | ***B*** | ***SE*** | ***p*** | ***β*** | ***B*** | ***SE*** | ***p*** | ***β*** |
| Female | -0.094 | 0.036 | 0.008 | -0.178 | -0.080 | 0.033 | 0.015 | -0.150 |
| Pre-vocational education | -0.010 | 0.040 | 0.795 | -0.020 | 0.052 | 0.042 | 0.211 | 0.098 |
| Immigrant background | 0.009 | 0.059 | 0.878 | 0.018 | 0.023 | 0.058 | 0.698 | 0.043 |
| SMU problems | | | | | -0.194 | 0.019 | <0.001 | -0.405 |
| SNS viewing | | | | | | | | |
| SNS viewing^2 | | | | | | | | |
| SNS posting | | | | | | | | |
| SNS posting^2 | | | | | | | | |
| SNS liking | | | | | | | | |
| SNS liking^2 | | | | | | | | |
| SNS responding | | | | | | | | |
| SNS responding^2 | | | | | | | | |
| IM viewing | | | | | | | | |
| IM viewing^2 | | | | | | | | |
| IM sending | -0.035 | 0.013 | 0.009 | -0.087 | 0.013 | 0.015 | 0.374 | 0.031 |
| IM sending^2 | 0.001 | 0.010 | 0.925 | 0.003 | 0.005 | 0.009 | 0.576 | 0.018 |
| **Random parameters** | **Est.** | ***SE*** | ***p*** | | **Est.** | ***SE*** | ***p*** | |
| Residual variance within | 0.402 | 0.013 | <0.001 | | 0.388 | 0.013 | <0.001 | |
| Residual variance between | 0.272 | 0.017 | <0.001 | | 0.235 | 0.015 | <0.001 | |
| **Explained variance** | **Est.** | | | | **Est.** | | | |
| $R^2$ within | 0.068 | | | | 0.095 | | | |
| $R^2$ between | 0.019 | | | | 0.164 | | | |
| **Fit statistics** | **Par.** | **Deviance** | **AIC** | **BIC** | **Deviance** | **LL** | **AIC** | **BIC** |
| Model fit | 11 | 12800.0 | 12822.0 | 12895.0 | 13 | 12476.7 | 12502.7 | 12589.1 |

*Notes.* SNS = social network sites; IM = instant messengers; SMU = social media use; Level 1 = yearly measurements; Level 2 = adolescents; *B* = unstandardized coefficient; *SE* = standard error, *p* = *p*-value; ***β*** = STDY-standardized for dichotomous variables (female, prevocational education, and immigrant background) and STDYX-standardized for the other variables; Est. = estimate; Par. = number of free parameters; Deviance = -2*loglikelihood; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion.

**Table A8.3**

*Random Effects Models, Life Satisfaction*

| | m5a | | | m6a | | |
|---|---|---|---|---|---|---|
| **Level 1 (*n* = 5,676)** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| Wave | -0.149 | 0.015 | <0.001 | -0.152 | 0.018 | <0.001 |
| SMU problems | | | | -0.105 | 0.011 | <0.001 |
| SNS viewing | -0.002 | 0.012 | 0.865 | 0.012 | 0.013 | 0.344 |
| SNS posting | | | | | | |
| SNS liking | | | | | | |
| SNS responding | | | | | | |
| IM viewing | | | | | | |
| IM sending | | | | | | |
| **Level 2 (*n* = 1,419)** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| Female | -0.092 | 0.038 | 0.015 | -0.085 | 0.034 | 0.012 |
| Pre-vocational education | 0.002 | 0.041 | 0.965 | 0.047 | 0.041 | 0.260 |
| Immigrant background | 0.020 | 0.059 | 0.735 | 0.020 | 0.058 | 0.738 |
| SMU problems | | | | -0.198 | 0.018 | <0.001 |
| SNS viewing | -0.036 | 0.018 | 0.049 | 0.022 | 0.017 | 0.193 |
| SNS posting | | | | | | |
| SNS liking | | | | | | |
| SNS responding | | | | | | |
| IM viewing | | | | | | |
| IM sending | | | | | | |
| **Random parameters** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| Residual variance within | 0.391 | 0.013 | <0.001 | 0.378 | 0.012 | <0.001 |
| Residual variance between | 0.275 | 0.017 | <0.001 | 0.237 | 0.015 | <0.001 |
| Variance slope | 0.008 | 0.004 | 0.036 | 0.006 | 0.004 | 0.107 |
| Covariance slope-intercept | 0.005 | 0.006 | 0.406 | 0.005 | 0.005 | 0.366 |
| **95% prediction intervals** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| LL-*B* | -0.172 | 0.043 | <0.001 | -0.140 | 0.051 | 0.006 |
| UL-*B* | 0.168 | 0.044 | <0.001 | 0.165 | 0.055 | 0.003 |
| LL-$\boldsymbol{\beta}$ | -0.296 | 0.073 | <0.001 | -0.242 | 0.088 | 0.006 |
| UL-$\boldsymbol{\beta}$ | 0.289 | 0.076 | <0.001 | 0.284 | 0.095 | 0.003 |
| **Fit statistics** | **Est.** | **Est.** | **Est.** | **Est.** | **Est.** | **Est.** |
| Free parameters | 11 | | | 13 | | |
| Deviance/AIC/BIC | 12804.2 | 12826.2 | 12899.3 | 12469.8 | 12495.8 | 12582.2 |
| **Model comparison**[1] | **Est.** | **Est.** | **Est.** | **Est.** | **Est.** | **Est.** |
| Δ Free parameters | 2 | | | 2 | | |
| Δ Deviance/AIC/BIC | -10.5 | -6.5 | 6.8 | -8.7 | -4.7 | 8.6 |
| *p*-value deviance | 0.005 | | | 0.013 | | |
| Corrected *p*-value[2] | 0.003 | | | 0.008 | | |

*Notes.* SNS = social network sites; IM = instant messengers; SMU = social media use; Level 1 = yearly measurements; Level 2 = adolescents; *B* = unstandardized coefficient; *SE* = standard error, *p* = *p*-value; LL = 95% prediction interval lower limit; UL = 95% prediction interval upper limit; $\boldsymbol{\beta}$ = STDYX-standardized; Est. = estimate; Deviance = -2*loglikelihood; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion.

[1] Model 5a was compared to Model 1a; Model 6a was compared to Model 2a.

[2] The *p*-value for the deviance was corrected to take into account the boundary of the slope variance parameter (Hox, 2010b; Stoel et al., 2006).

**Table A8.3 (continued)**

*Random Effects Models, Life Satisfaction*

| | m5b | | | m6b | | |
|---|---|---|---|---|---|---|
| **Level 1 (*n* = 5,676)** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| Wave | -0.152 | 0.014 | <0.001 | -0.149 | 0.015 | <0.001 |
| SMU problems | | | | -0.104 | 0.010 | <0.001 |
| SNS viewing | | | | | | |
| SNS posting | -0.012 | 0.008 | 0.164 | -0.008 | 0.009 | 0.396 |
| SNS liking | | | | | | |
| SNS responding | | | | | | |
| IM viewing | | | | | | |
| IM sending | | | | | | |
| **Level 2 (*n* = 1,419)** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| Female | -0.106 | 0.035 | 0.002 | -0.077 | 0.032 | 0.017 |
| Pre-vocational education | -0.001 | 0.038 | 0.978 | 0.049 | 0.040 | 0.223 |
| Immigrant background | 0.021 | 0.058 | 0.717 | 0.019 | 0.057 | 0.738 |
| SMU problems | | | | -0.193 | 0.018 | <0.001 |
| SNS viewing | | | | | | |
| SNS posting | -0.040 | 0.026 | 0.124 | 0.017 | 0.029 | 0.558 |
| SNS liking | | | | | | |
| SNS responding | | | | | | |
| IM viewing | | | | | | |
| IM sending | | | | | | |
| **Random parameters** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| Residual variance within | 0.394 | 0.012 | <0.001 | 0.379 | 0.011 | <0.001 |
| Residual variance between | 0.275 | 0.016 | <0.001 | 0.237 | 0.015 | <0.001 |
| Variance slope | 0.006 | 0.003 | 0.102 | 0.005 | 0.004 | 0.175 |
| Covariance slope-intercept | <0.001 | 0.007 | 0.955 | <0.001 | 0.008 | 0.979 |
| **95% prediction intervals** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| LL-*B* | -0.157 | 0.047 | 0.001 | -0.145 | 0.054 | 0.007 |
| UL-*B* | 0.133 | 0.047 | 0.005 | 0.130 | 0.058 | 0.025 |
| LL-***β*** | -0.271 | 0.081 | 0.001 | -0.253 | 0.094 | 0.007 |
| UL-***β*** | 0.231 | 0.081 | 0.005 | 0.226 | 0.101 | 0.025 |
| **Fit statistics** | **Est.** | **Est.** | **Est.** | **Est.** | **Est.** | **Est.** |
| Free parameters | 11 | | | 13 | | |
| Deviance/AIC/BIC | 12806.3 | 12828.3 | 12901.4 | 12472.8 | 12498.8 | 12585.1 |
| **Model comparison**[1] | **Est.** | **Est.** | **Est.** | **Est.** | **Est.** | **Est.** |
| Δ Free parameters | 2 | | | 2 | | |
| Δ Deviance/AIC/BIC | -8.6 | -4.6 | 8.7 | -8.9 | -4.9 | 8.4 |
| *p*-value deviance | 0.014 | | | 0.012 | | |
| Corrected *p*-value[2] | 0.009 | | | 0.007 | | |

*Notes.* SNS = social network sites; IM = instant messengers; SMU = social media use; Level 1 = yearly measurements; Level 2 = adolescents; *B* = unstandardized coefficient; *SE* = standard error, *p* = *p*-value; LL = 95% prediction interval lower limit; UL = 95% prediction interval upper limit; *β* = STDYX-standardized; Est. = estimate; Deviance = -2*loglikelihood; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion.

[1] Model 5b was compared to Model 1b; Model 6b was compared to Model 2b.

[2] The *p*-value for the deviance was corrected to take into account the boundary of the slope variance parameter (Hox, 2010b; Stoel et al., 2006).

**Table A8.3 (continued)**

*Random Effects Models, Life Satisfaction*

| | **m5c** | | | **m6c** | | |
|---|---|---|---|---|---|---|
| **Level 1 (*n* = 5,676)** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| Wave | -0.150 | 0.014 | <0.001 | -0.149 | 0.015 | <0.001 |
| SMU problems | | | | -0.104 | 0.010 | <0.001 |
| SNS viewing | | | | | | |
| SNS posting | | | | | | |
| SNS liking | -0.004 | 0.007 | 0.602 | 0.004 | 0.007 | 0.613 |
| SNS responding | | | | | | |
| IM viewing | | | | | | |
| IM sending | | | | | | |
| **Level 2 (*n* = 1,419)** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| Female | -0.094 | 0.038 | 0.013 | -0.085 | 0.034 | 0.014 |
| Pre-vocational education | -0.013 | 0.041 | 0.745 | 0.055 | 0.042 | 0.193 |
| Immigrant background | 0.011 | 0.059 | 0.846 | 0.023 | 0.058 | 0.695 |
| SMU problems | | | | -0.194 | 0.020 | <0.001 |
| SNS viewing | | | | | | |
| SNS posting | | | | | | |
| SNS liking | -0.014 | 0.013 | 0.275 | 0.016 | 0.014 | 0.239 |
| SNS responding | | | | | | |
| IM viewing | | | | | | |
| IM sending | | | | | | |
| **Random parameters** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| Residual variance within | 0.391 | 0.013 | <0.001 | 0.376 | 0.014 | <0.001 |
| Residual variance between | 0.276 | 0.017 | <0.001 | 0.237 | 0.015 | <0.001 |
| Variance slope | 0.005 | 0.003 | 0.054 | 0.005 | 0.002 | 0.039 |
| Covariance slope-intercept | 0.011 | 0.005 | 0.046 | 0.008 | 0.005 | 0.094 |
| **95% prediction intervals** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| LL-*B* | -0.145 | 0.038 | <0.001 | -0.133 | 0.035 | <0.001 |
| UL-*B* | 0.137 | 0.039 | <0.001 | 0.140 | 0.035 | <0.001 |
| LL-***β*** | -0.303 | 0.080 | <0.001 | -0.280 | 0.074 | <0.001 |
| UL-***β*** | 0.288 | 0.081 | <0.001 | 0.295 | 0.074 | <0.001 |
| **Fit statistics** | **Est.** | **Est.** | **Est.** | **Est.** | **Est.** | **Est.** |
| Free parameters | 11 | | | 13 | | |
| Deviance/AIC/BIC | 12801.6 | 12823.6 | 12896.6 | 12466.1 | 12492.1 | 12578.5 |
| **Model comparison[1]** | **Est.** | **Est.** | **Est.** | **Est.** | **Est.** | **Est.** |
| Δ Free parameters | 2 | | | 2 | | |
| Δ Deviance/AIC/BIC | -18.4 | -14.4 | -1.1 | -15.5 | -11.5 | 1.8 |
| *p*-value deviance | <0.001 | | | <0.001 | | |
| Corrected *p*-value[2] | <0.001 | | | <0.001 | | |

*Notes.* SNS = social network sites; IM = instant messengers; SMU = social media use; Level 1 = yearly measurements; Level 2 = adolescents; *B* = unstandardized coefficient; *SE* = standard error, *p* = *p*-value; LL = 95% prediction interval lower limit; UL = 95% prediction interval upper limit; ***β*** = STDYX-standardized; Est. = estimate; Deviance = -2*loglikelihood; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion.

[1] Model 5c was compared to Model 1c; Model 6c was compared to Model 2c.

[2] The *p*-value for the deviance was corrected to take into account the boundary of the slope variance parameter (Hox, 2010b; Stoel et al., 2006).

**Table A8.3 (continued)**

*Random Effects Models, Life Satisfaction*

| | m5d | | | m6d | | |
|---|---|---|---|---|---|---|
| **Level 1 (*n* = 5,676)** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| Wave | -0.148 | 0.015 | <0.001 | -0.147 | 0.016 | <0.001 |
| SMU problems | | | | -0.102 | 0.010 | <0.001 |
| SNS viewing | | | | | | |
| SNS posting | | | | | | |
| SNS liking | | | | | | |
| SNS responding | -0.021 | 0.012 | 0.065 | -0.011 | 0.013 | 0.377 |
| IM viewing | | | | | | |
| IM sending | | | | | | |
| **Level 2 (*n* = 1,419)** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| Female | -0.091 | 0.041 | 0.026 | -0.098 | 0.037 | 0.007 |
| Pre-vocational education | -0.012 | 0.041 | 0.778 | 0.042 | 0.043 | 0.325 |
| Immigrant background | 0.017 | 0.059 | 0.769 | 0.023 | 0.059 | 0.694 |
| SMU problems | | | | -0.197 | 0.017 | <0.001 |
| SNS viewing | | | | | | |
| SNS posting | | | | | | |
| SNS liking | | | | | | |
| SNS responding | -0.013 | 0.016 | 0.433 | 0.027 | 0.016 | 0.081 |
| IM viewing | | | | | | |
| IM sending | | | | | | |
| **Random parameters** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| Residual variance within | 0.388 | 0.012 | <0.001 | 0.374 | 0.013 | <0.001 |
| Residual variance between | 0.277 | 0.017 | <0.001 | 0.237 | 0.015 | <0.001 |
| Variance slope | 0.006 | 0.002 | 0.008 | 0.006 | 0.002 | 0.005 |
| Covariance slope-intercept | 0.009 | 0.006 | 0.092 | 0.005 | 0.005 | 0.316 |
| **95% prediction intervals** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| LL-*B* | -0.178 | 0.034 | <0.001 | -0.161 | 0.032 | <0.001 |
| UL-*B* | 0.135 | 0.029 | <0.001 | 0.139 | 0.028 | <0.001 |
| LL-***β*** | -0.361 | 0.068 | <0.001 | -0.328 | 0.064 | <0.001 |
| UL-***β*** | 0.275 | 0.060 | <0.001 | 0.283 | 0.057 | <0.001 |
| **Fit statistics** | **Est.** | **Est.** | **Est.** | **Est.** | **Est.** | **Est.** |
| Free parameters | 11 | | | 13 | | |
| Deviance/AIC/BIC | 12791.1 | 12813.1 | 12886.2 | 12461.3 | 12487.3 | 12573.6 |
| **Model comparison[1]** | **Est.** | **Est.** | **Est.** | **Est.** | **Est.** | **Est.** |
| Δ Free parameters | 2 | | | 2 | | |
| Δ Deviance/AIC/BIC | -17.3 | -13.3 | -0.1 | -13.0 | -9.0 | 4.3 |
| *p*-value deviance | <0.001 | | | 0.001 | | |
| Corrected *p*-value[2] | <0.001 | | | 0.001 | | |

*Notes.* SNS = social network sites; IM = instant messengers; SMU = social media use; Level 1 = yearly measurements; Level 2 = adolescents; *B* = unstandardized coefficient; *SE* = standard error, *p* = *p*-value; LL = 95% prediction interval lower limit; UL = 95% prediction interval upper limit; ***β*** = STDYX-standardized; Est. = estimate; Deviance = -2*loglikelihood; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion.

[1] Model 5d was compared to Model 1d; Model 6d was compared to Model 2d.

[2] The *p*-value for the deviance was corrected to take into account the boundary of the slope variance parameter (Hox, 2010b; Stoel et al., 2006).

**Table A8.3 (continued)**

*Random Effects Models, Life Satisfaction*

| | m5e | | | m6e | | |
|---|---|---|---|---|---|---|
| **Level 1 (*n* = 5,676)** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| Wave | -0.147 | 0.014 | <0.001 | -0.148 | 0.016 | <0.001 |
| SMU problems | | | | -0.105 | 0.010 | <0.001 |
| SNS viewing | | | | | | |
| SNS posting | | | | | | |
| SNS liking | | | | | | |
| SNS responding | | | | | | |
| IM viewing | -0.011 | 0.011 | 0.324 | 0.008 | 0.011 | 0.469 |
| IM sending | | | | | | |
| **Level 2 (*n* = 1,419)** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| Female | -0.095 | 0.036 | 0.008 | -0.081 | 0.033 | 0.013 |
| Pre-vocational education | <0.001 | 0.041 | 0.997 | 0.053 | 0.042 | 0.209 |
| Immigrant background | 0.008 | 0.058 | 0.893 | 0.024 | 0.058 | 0.678 |
| SMU problems | | | | -0.196 | 0.020 | <0.001 |
| SNS viewing | | | | | | |
| SNS posting | | | | | | |
| SNS liking | | | | | | |
| SNS responding | | | | | | |
| IM viewing | -0.046 | 0.015 | 0.002 | 0.016 | 0.016 | 0.313 |
| IM sending | | | | | | |
| **Random parameters** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| Residual variance within | 0.387 | 0.016 | <0.001 | 0.373 | 0.015 | <0.001 |
| Residual variance between | 0.275 | 0.017 | <0.001 | 0.239 | 0.015 | <0.001 |
| Variance slope | 0.012 | 0.004 | 0.003 | 0.011 | 0.004 | 0.006 |
| Covariance slope-intercept | 0.008 | 0.007 | 0.296 | 0.005 | 0.006 | 0.351 |
| **95% prediction intervals** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| LL-*B* | -0.226 | 0.037 | <0.001 | -0.198 | 0.038 | <0.001 |
| UL-*B* | 0.203 | 0.039 | <0.001 | 0.215 | 0.041 | <0.001 |
| LL-***β*** | -0.349 | 0.058 | <0.001 | -0.308 | 0.059 | <0.001 |
| UL-***β*** | 0.314 | 0.061 | <0.001 | 0.334 | 0.064 | <0.001 |
| **Fit statistics** | **Est.** | **Est.** | **Est.** | **Est.** | **Est.** | **Est.** |
| Free parameters | 11 | | | 13 | | |
| Deviance/AIC/BIC | 12790.3 | 12812.3 | 12885.4 | 12466.4 | 12492.4 | 12578.8 |
| **Model comparison[1]** | **Est.** | **Est.** | **Est.** | **Est.** | **Est.** | **Est.** |
| Δ Free parameters | 2 | | | 2 | | |
| Δ Deviance/AIC/BIC | -18.1 | -14.1 | -0.8 | -15.8 | -11.8 | 1.5 |
| *p*-value deviance | <0.001 | | | <0.001 | | |
| Corrected *p*-value[2] | <0.001 | | | <0.001 | | |

*Notes.* SNS = social network sites; IM = instant messengers; SMU = social media use; Level 1 = yearly measurements; Level 2 = adolescents; *B* = unstandardized coefficient; *SE* = standard error, *p* = *p*-value; LL = 95% prediction interval lower limit; UL = 95% prediction interval upper limit; ***β*** = STDYX-standardized; Est. = estimate; Deviance = -2*loglikelihood; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion.

[1] Model 5e was compared to Model 1e; Model 6e was compared to Model 2e.

[2] The *p*-value for the deviance was corrected to take into account the boundary of the slope variance parameter (Hox, 2010b; Stoel et al., 2006).

**Table A8.3 (continued)**

*Random Effects Models, Life Satisfaction*

| | m5f | | | m6f | | |
|---|---|---|---|---|---|---|
| **Level 1 (*n* = 5,676)** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| Wave | -0.148 | 0.014 | <0.001 | -0.147 | 0.015 | <0.001 |
| SMU problems | | | | -0.101 | 0.009 | <0.001 |
| SNS viewing | | | | | | |
| SNS posting | | | | | | |
| SNS liking | | | | | | |
| SNS responding | | | | | | |
| IM viewing | | | | | | |
| IM sending | -0.024 | 0.012 | 0.052 | -0.011 | 0.012 | 0.393 |
| **Level 2 (*n* = 1,419)** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| Female | -0.089 | 0.036 | 0.013 | -0.078 | 0.033 | 0.018 |
| Pre-vocational education | -0.007 | 0.040 | 0.868 | 0.055 | 0.041 | 0.186 |
| Immigrant background | 0.007 | 0.060 | 0.908 | 0.021 | 0.059 | 0.717 |
| SMU problems | | | | -0.192 | 0.019 | <0.001 |
| SNS viewing | | | | | | |
| SNS posting | | | | | | |
| SNS liking | | | | | | |
| SNS responding | | | | | | |
| IM viewing | | | | | | |
| IM sending | -0.035 | 0.013 | 0.008 | 0.012 | 0.014 | 0.424 |
| **Random parameters** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| Residual variance within | 0.391 | 0.014 | <0.001 | 0.378 | 0.015 | <0.001 |
| Residual variance between | 0.275 | 0.017 | <0.001 | 0.237 | 0.015 | <0.001 |
| Variance slope | 0.007 | 0.004 | 0.064 | 0.005 | 0.003 | 0.111 |
| Covariance slope-intercept | 0.016 | 0.006 | 0.004 | 0.012 | 0.005 | 0.013 |
| **95% prediction intervals** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| LL-*B* | -0.182 | 0.046 | <0.001 | -0.153 | 0.049 | 0.002 |
| UL-*B* | 0.135 | 0.046 | 0.004 | 0.132 | 0.048 | 0.006 |
| LL-***β*** | -0.320 | 0.080 | <0.001 | -0.271 | 0.087 | 0.002 |
| UL-***β*** | 0.237 | 0.081 | 0.004 | 0.233 | 0.085 | 0.006 |
| **Fit statistics** | **Est.** | **Est.** | **Est.** | **Est.** | **Est.** | **Est.** |
| Free parameters | 11 | | | 13 | | |
| Deviance/AIC/BIC | 12781.7 | 12803.7 | 12876.8 | 12465.5 | 12491.5 | 12577.9 |
| **Model comparison[1]** | **Est.** | **Est.** | **Est.** | **Est.** | **Est.** | **Est.** |
| Δ Free parameters | 2 | | | 2 | | |
| Δ Deviance/AIC/BIC | -20.9 | -16.9 | -3.6 | -14.8 | -10.8 | 2.5 |
| *p*-value deviance | <0.001 | | | 0.001 | | |
| Corrected *p*-value[2] | <0.001 | | | <0.001 | | |

*Notes.* SNS = social network sites; IM = instant messengers; SMU = social media use; Level 1 = yearly measurements; Level 2 = adolescents; *B* = unstandardized coefficient; *SE* = standard error, *p* = *p*-value; LL = 95% prediction interval lower limit; UL = 95% prediction interval upper limit; ***β*** = STDYX-standardized; Est. = estimate; Deviance = -2*loglikelihood; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion.

[1] Model 5f was compared to Model 1f; Model 6f was compared to Model 2f.

[2] The *p*-value for the deviance was corrected to take into account the boundary of the slope variance parameter (Hox, 2010b; Stoel et al., 2006).

8

**Table A8.4**

*Random Effects Models with Social Comparison as Moderator, Life Satisfaction*

| | m7a | | | m8a | | |
|---|---|---|---|---|---|---|
| **Level 1 (*n* = 5,676)** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| Wave | -0.149 | 0.015 | <0.001 | -0.152 | 0.018 | <0.001 |
| SMU problems | | | | -0.105 | 0.011 | <0.001 |
| SNS viewing | -0.002 | 0.011 | 0.862 | 0.013 | 0.013 | 0.339 |
| SNS posting | | | | | | |
| SNS liking | | | | | | |
| SNS responding | | | | | | |
| IM viewing | | | | | | |
| IM sending | | | | | | |
| **Level 2 (*n* = 1,419)** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| Female | 0.020 | 0.032 | 0.536 | 0.002 | 0.031 | 0.957 |
| Pre-vocational education | -0.069 | 0.042 | 0.103 | -0.029 | 0.044 | 0.513 |
| Immigrant background | 0.006 | 0.059 | 0.913 | 0.009 | 0.058 | 0.880 |
| Social comparison | -0.444 | 0.031 | <0.001 | -0.356 | 0.033 | <0.001 |
| SMU problems | | | | -0.118 | 0.016 | <0.001 |
| SNS viewing | 0.005 | 0.017 | 0.785 | 0.031 | 0.016 | 0.046 |
| SNS posting | | | | | | |
| SNS liking | | | | | | |
| SNS responding | | | | | | |
| IM viewing | | | | | | |
| IM sending | | | | | | |
| **Cross-level interactions** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| SNS viewing * social comparison | -0.006 | 0.019 | 0.745 | 0.002 | 0.018 | 0.926 |
| SNS posting * social comparison | | | | | | |
| SNS liking * social comparison | | | | | | |
| SNS responding * social comparison | | | | | | |
| IM viewing * social comparison | | | | | | |
| IM sending * social comparison | | | | | | |
| **Random parameters** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| Residual variance within | 0.391 | 0.013 | <0.001 | 0.378 | 0.012 | <0.001 |
| Residual variance between | 0.212 | 0.013 | <0.001 | 0.203 | 0.013 | <0.001 |
| Residual variance slope | 0.008 | 0.004 | 0.034 | 0.006 | 0.004 | 0.104 |
| Covariance slope-intercept | 0.005 | 0.005 | 0.377 | 0.005 | 0.005 | 0.360 |
| **Fit statistics** | **Est.** | **Est.** | **Est.** | **Est.** | **Est.** | **Est.** |
| Free parameters | 13 | | | 15 | | |
| Deviance/AIC/BIC | 12540.8 | 12566.8 | 12653.2 | 12316.3 | 12346.3 | 12446.0 |

*Notes*. SNS = social network sites; IM = instant messengers; SMU = social media use; Level 1 = yearly measurements; Level 2 = adolescents; *B* = unstandardized coefficient; *SE* = standard error, *p* = *p*-value; Est. = estimate; Deviance = -2*loglikelihood; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion.

**Table A8.4 (continued)**

*Random Effects Models with Social Comparison as Moderator, Life Satisfaction*

| | m7b | | | m8b | | |
|---|---|---|---|---|---|---|
| **Level 1 (*n* = 5,676)** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| Wave | -0.152 | 0.014 | <0.001 | -0.149 | 0.015 | <0.001 |
| SMU problems | | | | -0.104 | 0.010 | <0.001 |
| SNS viewing | | | | | | |
| SNS posting | -0.012 | 0.008 | 0.159 | -0.008 | 0.009 | 0.389 |
| SNS liking | | | | | | |
| SNS responding | | | | | | |
| IM viewing | | | | | | |
| IM sending | | | | | | |
| **Level 2 (*n* = 1,419)** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| Female | 0.020 | 0.031 | 0.519 | 0.011 | 0.030 | 0.722 |
| Pre-vocational education | -0.061 | 0.042 | 0.145 | -0.020 | 0.043 | 0.642 |
| Immigrant background | 0.007 | 0.057 | 0.902 | 0.009 | 0.057 | 0.878 |
| Social comparison | -0.440 | 0.029 | <0.001 | -0.352 | 0.032 | <0.001 |
| SMU problems | | | | -0.110 | 0.017 | <0.001 |
| SNS viewing | | | | | | |
| SNS posting | -0.014 | 0.024 | 0.558 | 0.014 | 0.026 | 0.599 |
| SNS liking | | | | | | |
| SNS responding | | | | | | |
| IM viewing | | | | | | |
| IM sending | | | | | | |
| **Cross-level interactions** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| SNS viewing * social comparison | | | | | | |
| SNS posting * social comparison | -0.013 | 0.015 | 0.377 | -0.011 | 0.016 | 0.481 |
| SNS liking * social comparison | | | | | | |
| SNS responding * social comparison | | | | | | |
| IM viewing * social comparison | | | | | | |
| IM sending * social comparison | | | | | | |
| **Random parameters** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| Residual variance within | 0.394 | 0.012 | <0.001 | 0.379 | 0.011 | <0.001 |
| Residual variance between | 0.211 | 0.013 | <0.001 | 0.204 | 0.013 | <0.001 |
| Residual variance slope | 0.006 | 0.004 | 0.107 | 0.005 | 0.004 | 0.179 |
| Covariance slope-intercept | -0.001 | 0.007 | 0.886 | -0.001 | 0.008 | 0.907 |
| **Fit statistics** | **Est.** | **Est.** | **Est.** | **Est.** | **Est.** | **Est.** |
| Free parameters | 13 | | | 15 | | |
| Deviance/AIC/BIC | 12539.9 | 12565.9 | 12652.3 | 12322.5 | 12352.5 | 12452.2 |

*Notes.* SNS = social network sites; IM = instant messengers; SMU = social media use; Level 1 = yearly measurements; Level 2 = adolescents; *B* = unstandardized coefficient; *SE* = standard error, *p* = *p*-value; Est. = estimate; Deviance = -2*loglikelihood; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion.

8

**Table A8.4 (continued)**

*Random Effects Models with Social Comparison as Moderator, Life Satisfaction*

| | m7c | | | m8c | | |
|---|---|---|---|---|---|---|
| **Level 1 (*n* = 5,676)** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| Wave | -0.150 | 0.014 | <0.001 | -0.149 | 0.015 | <0.001 |
| SMU problems | | | | -0.103 | 0.010 | <0.001 |
| SNS viewing | | | | | | |
| SNS posting | | | | | | |
| SNS liking | -0.005 | 0.007 | 0.509 | 0.003 | 0.007 | 0.709 |
| SNS responding | | | | | | |
| IM viewing | | | | | | |
| IM sending | | | | | | |
| **Level 2 (*n* = 1,419)** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| Female | 0.012 | 0.032 | 0.706 | -0.003 | 0.032 | 0.918 |
| Pre-vocational education | -0.072 | 0.042 | 0.092 | -0.020 | 0.044 | 0.655 |
| Immigrant background | 0.010 | 0.059 | 0.859 | 0.017 | 0.058 | 0.765 |
| Social comparison | -0.453 | 0.031 | <0.001 | -0.364 | 0.032 | <0.001 |
| SMU problems | | | | -0.114 | 0.017 | <0.001 |
| SNS viewing | | | | | | |
| SNS posting | | | | | | |
| SNS liking | 0.019 | 0.013 | 0.136 | 0.031 | 0.013 | 0.021 |
| SNS responding | | | | | | |
| IM viewing | | | | | | |
| IM sending | | | | | | |
| **Cross-level interactions** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| SNS viewing * social comparison | | | | | | |
| SNS posting * social comparison | | | | | | |
| SNS liking * social comparison | -0.030 | 0.013 | 0.025 | -0.027 | 0.013 | 0.035 |
| SNS responding * social comparison | | | | | | |
| IM viewing * social comparison | | | | | | |
| IM sending * social comparison | | | | | | |
| **Random parameters** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| Residual variance within | 0.390 | 0.013 | <0.001 | 0.376 | 0.014 | <0.001 |
| Residual variance between | 0.211 | 0.014 | <0.001 | 0.203 | 0.014 | <0.001 |
| Residual variance slope | 0.005 | 0.003 | 0.054 | 0.005 | 0.002 | 0.035 |
| Covariance slope-intercept | 0.007 | 0.005 | 0.130 | 0.006 | 0.004 | 0.158 |
| **Fit statistics** | **Est.** | **Est.** | **Est.** | **Est.** | **Est.** | **Est.** |
| Free parameters | 13 | | | 15 | | |
| Deviance/AIC/BIC | 12526.3 | 12552.3 | 12638.7 | 12304.7 | 12334.7 | 12434.3 |

*Notes*. SNS = social network sites; IM = instant messengers; SMU = social media use; Level 1 = yearly measurements; Level 2 = adolescents; *B* = unstandardized coefficient; *SE* = standard error, *p* = *p*-value; Est. = estimate; Deviance = -2*loglikelihood; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion.

**Table A8.4 (continued)**

*Random Effects Models with Social Comparison as Moderator, Life Satisfaction*

| | m7d | | | m8d | | |
|---|---|---|---|---|---|---|
| **Level 1 (*n* = 5,676)** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| Wave | -0.147 | 0.015 | <0.001 | -0.146 | 0.016 | <0.001 |
| SMU problems | | | | -0.101 | 0.010 | <0.001 |
| SNS viewing | | | | | | |
| SNS posting | | | | | | |
| SNS liking | | | | | | |
| SNS responding | -0.021 | 0.012 | 0.076 | -0.011 | 0.013 | 0.403 |
| IM viewing | | | | | | |
| IM sending | | | | | | |
| **Level 2 (*n* = 1,419)** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| Female | 0.005 | 0.034 | 0.883 | -0.019 | 0.034 | 0.575 |
| Pre-vocational education | -0.082 | 0.042 | 0.052 | -0.036 | 0.044 | 0.412 |
| Immigrant background | 0.009 | 0.059 | 0.879 | 0.014 | 0.059 | 0.810 |
| Social comparison | -0.452 | 0.030 | <0.001 | -0.362 | 0.032 | <0.001 |
| SMU problems | | | | -0.116 | 0.017 | <0.001 |
| SNS viewing | | | | | | |
| SNS posting | | | | | | |
| SNS liking | | | | | | |
| SNS responding | 0.023 | 0.016 | 0.139 | 0.040 | 0.015 | 0.009 |
| IM viewing | | | | | | |
| IM sending | | | | | | |
| **Cross-level interactions** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| SNS viewing * social comparison | | | | | | |
| SNS posting * social comparison | | | | | | |
| SNS liking * social comparison | | | | | | |
| SNS responding * social comparison | -0.025 | 0.019 | 0.185 | -0.023 | 0.018 | 0.217 |
| IM viewing * social comparison | | | | | | |
| IM sending * social comparison | | | | | | |
| **Random parameters** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| Residual variance within | 0.388 | 0.012 | <0.001 | 0.374 | 0.013 | <0.001 |
| Residual variance between | 0.212 | 0.014 | <0.001 | 0.203 | 0.014 | <0.001 |
| Residual variance slope | 0.006 | 0.002 | 0.012 | 0.006 | 0.002 | 0.008 |
| Covariance slope-intercept | 0.007 | 0.005 | 0.224 | 0.004 | 0.005 | 0.434 |
| **Fit statistics** | **Est.** | **Est.** | **Est.** | **Est.** | **Est.** | **Est.** |
| Free parameters | 13 | | | 15 | | |
| Deviance/AIC/BIC | 12514.7 | 12540.7 | 12627.0 | 12299.8 | 12329.8 | 12429.5 |

*Notes.* SNS = social network sites; IM = instant messengers; SMU = social media use; Level 1 = yearly measurements; Level 2 = adolescents; *B* = unstandardized coefficient; *SE* = standard error, *p* = *p*-value; Est. = estimate; Deviance = -2*loglikelihood; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion.

**Table A8.4 (continued)**

*Random Effects Models with Social Comparison as Moderator, Life Satisfaction*

| | m7e | | | m8e | | |
|---|---|---|---|---|---|---|
| **Level 1 (*n* = 5,676)** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| Wave | -0.147 | 0.014 | <0.001 | -0.148 | 0.016 | <0.001 |
| SMU problems | | | | -0.105 | 0.010 | <0.001 |
| SNS viewing | | | | | | |
| SNS posting | | | | | | |
| SNS liking | | | | | | |
| SNS responding | | | | | | |
| IM viewing | -0.011 | 0.011 | 0.320 | 0.008 | 0.012 | 0.472 |
| IM sending | | | | | | |
| **Level 2 (*n* = 1,419)** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| Female | 0.020 | 0.031 | 0.523 | 0.006 | 0.031 | 0.842 |
| Pre-vocational education | -0.066 | 0.044 | 0.132 | -0.021 | 0.045 | 0.632 |
| Immigrant background | 0.006 | 0.058 | 0.911 | 0.017 | 0.058 | 0.774 |
| Social comparison | -0.442 | 0.032 | <0.001 | -0.357 | 0.032 | <0.001 |
| SMU problems | | | | -0.117 | 0.018 | <0.001 |
| SNS viewing | | | | | | |
| SNS posting | | | | | | |
| SNS liking | | | | | | |
| SNS responding | | | | | | |
| IM viewing | <0.001 | 0.015 | 0.992 | 0.028 | 0.015 | 0.059 |
| IM sending | | | | | | |
| **Cross-level interactions** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| SNS viewing * social comparison | | | | | | |
| SNS posting * social comparison | | | | | | |
| SNS liking * social comparison | | | | | | |
| SNS responding * social comparison | | | | | | |
| IM viewing * social comparison | -0.007 | 0.018 | 0.684 | 0.002 | 0.018 | 0.929 |
| IM sending * social comparison | | | | | | |
| **Random parameters** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| Residual variance within | 0.387 | 0.016 | <0.001 | 0.373 | 0.015 | <0.001 |
| Residual variance between | 0.213 | 0.014 | <0.001 | 0.205 | 0.013 | <0.001 |
| Residual variance slope | 0.012 | 0.004 | 0.003 | 0.011 | 0.004 | 0.006 |
| Covariance slope-intercept | 0.006 | 0.006 | 0.297 | 0.005 | 0.005 | 0.326 |
| **Fit statistics** | **Est.** | **Est.** | **Est.** | **Est.** | **Est.** | **Est.** |
| Free parameters | 13 | | | 15 | | |
| Deviance/AIC/BIC | 12532.3 | 12558.3 | 12644.7 | 12313.1 | 12343.1 | 12442.7 |

*Notes*. SNS = social network sites; IM = instant messengers; SMU = social media use; Level 1 = yearly measurements; Level 2 = adolescents; *B* = unstandardized coefficient; *SE* = standard error, *p* = *p*-value; Est. = estimate; Deviance = -2*loglikelihood; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion.

**Table A8.4 (continued)**

*Random Effects Models with Social Comparison as Moderator, Life Satisfaction*

| | m7f | | | m8f | | |
|---|---|---|---|---|---|---|
| **Level 1 (*n* = 5,676)** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| Wave | -0.148 | 0.014 | <0.001 | -0.147 | 0.015 | <0.001 |
| SMU problems | | | | -0.101 | 0.009 | <0.001 |
| SNS viewing | | | | | | |
| SNS posting | | | | | | |
| SNS liking | | | | | | |
| SNS responding | | | | | | |
| IM viewing | | | | | | |
| IM sending | -0.024 | 0.012 | 0.051 | -0.011 | 0.013 | 0.388 |
| **Level 2 (*n* = 1,419)** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| Female | 0.023 | 0.031 | 0.466 | 0.007 | 0.031 | 0.810 |
| Pre-vocational education | -0.066 | 0.042 | 0.118 | -0.019 | 0.043 | 0.667 |
| Immigrant background | 0.005 | 0.059 | 0.930 | 0.014 | 0.058 | 0.808 |
| Social comparison | -0.444 | 0.032 | <0.001 | -0.358 | 0.033 | <0.001 |
| SMU problems | | | | -0.113 | 0.018 | <0.001 |
| SNS viewing | | | | | | |
| SNS posting | | | | | | |
| SNS liking | | | | | | |
| SNS responding | | | | | | |
| IM viewing | | | | | | |
| IM sending | 0.003 | 0.013 | 0.842 | 0.023 | 0.014 | 0.103 |
| **Cross-level interactions** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| SNS viewing * social comparison | | | | | | |
| SNS posting * social comparison | | | | | | |
| SNS liking * social comparison | | | | | | |
| SNS responding * social comparison | | | | | | |
| IM viewing * social comparison | | | | | | |
| IM sending * social comparison | -0.024 | 0.017 | 0.153 | -0.019 | 0.017 | 0.263 |
| **Random parameters** | ***B*** | ***SE*** | ***p*** | ***B*** | ***SE*** | ***p*** |
| Residual variance within | 0.391 | 0.014 | <0.001 | 0.378 | 0.014 | <0.001 |
| Residual variance between | 0.212 | 0.013 | <0.001 | 0.203 | 0.013 | <0.001 |
| Residual variance slope | 0.006 | 0.004 | 0.069 | 0.005 | 0.003 | 0.109 |
| Covariance slope-intercept | 0.013 | 0.006 | 0.018 | 0.011 | 0.005 | 0.026 |
| **Fit statistics** | **Est.** | **Est.** | **Est.** | **Est.** | **Est.** | **Est.** |
| Free parameters | 13 | | | 15 | | |
| Deviance/AIC/BIC | 12518.1 | 12544.1 | 12630.5 | 12310.7 | 12340.7 | 12440.3 |

*Notes.* SNS = social network sites; IM = instant messengers; SMU = social media use; Level 1 = yearly measurements; Level 2 = adolescents; *B* = unstandardized coefficient; *SE* = standard error, *p* = *p*-value; Est. = estimate; Deviance = -2*loglikelihood; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion.

# CHAPTER 9

## SUMMARY AND DISCUSSION

## Summary and Discussion

The aim of the present dissertation was to enhance current knowledge on the association between social media use (SMU) and adolescent wellbeing. More specifically, we focused on the differences between SMU problems and SMU intensity, in particular in their differential associations with wellbeing. Throughout the dissertation, wellbeing most often refers to mental health, assessed by indicators of positive mental health (i.e., life satisfaction, self-esteem), as well as mental health problems (i.e., depressive symptoms, symptoms of attention deficit hyperactivity disorder (ADHD), psychosomatic complaints, and emotional, peer, and conduct problems). In addition, we also studied other domains related to adolescent wellbeing, namely social wellbeing (i.e., friends and family support, face-to-face contact with friends, perceived friendship competence), school wellbeing (i.e., school satisfaction, perceived schoolwork pressure), and sleep (i.e., sleep duration and sleep quality).

In this final chapter, we first summarize the main findings by chapter. Subsequently, we integrate the findings from the chapters intro six key findings. After that, we discuss the implications of our findings, divided into conceptual, methodological, theoretical, and practical implications. Then, we discuss four future research directions that emerged from our studies and we outline the strength and limitations from our studies. Finally, we end this chapter with a conclusion.

## Summary of the Main Findings by Chapter

There is little large-scale validation research on instruments measuring problematic SMU. **Chapter 2** investigated the psychometric properties of the nine-item Social Media Disorder (SMD)-scale within a nationally representative cross-sectional sample of 6,626 Dutch adolescents. Findings showed that the scale had a solid unidimensional factor structure, confirming structural validity. Also, the items showed high internal consistency, suggesting good reliability. The scale showed to be most informative at moderate to high scores on the scale's continuum, which implies that the scale measures moderate to high levels of SMU problems most reliably. In addition, the factor structure was measurement invariant across gender, age, ethnic backgrounds, and educational levels. Three subgroups of adolescents with different patterns of SMU problems were identified: A normative (i.e., reporting no symptoms or one symptom), at-risk (i.e., reporting two to five symptoms), and problematic (i.e., reporting six to nine symptoms) group. Higher scores on the SMD-scale were associated with a greater probability of reporting problems related to mental health, school, and sleep, which confirmed criterion validity. Together, these findings indicate that the SMD-scale is suitable for assessing problematic SMU among Dutch adolescents.

There is no scale that measures problematic SMU for which its psychometric properties have been investigated and compared across various national settings. Building on the previous chapter, **Chapter 3** validated the SMD-scale using large-scale cross-sectional nationally representative data from 222,532 adolescents from 44 countries within the European region and Canada. Results confirmed good structural validity of a unidimensional scale in all countries. Also, the internal consistency of the items was good in all countries, indicating that the scores on the scale are reliable. In addition, the factor structure of the scale was measurement invariant across countries, gender, socioeconomic status, and age, with the exception that age invariance was not established in one country. In almost all countries, problematic SMU was positively related to higher SMU intensity, indicated by the intensity of online communication, and negatively with mental health[6], indicated by life satisfaction and psychosomatic complaints, suggesting appropriate criterion validity. Overall, the study demonstrated that the SMD-scale has good psychometric properties in many national contexts, facilitating future (cross-national) research on problematic SMU.



Studies on the association between SMU behaviors and wellbeing typically rely on single-country data, leaving the question whether these associations are country-specific unanswered. **Chapter 4** focused on the question whether intense SMU (i.e., engaging in online communication throughout the whole day) and problematic SMU and their associations with mental[7], school, and social wellbeing indicators depended upon the country context using international cross-sectional data. Furthermore, it examined whether differences in intense and problematic SMU across countries could be

[6] In Chapter 3, we referred to mental wellbeing instead of mental health.

[7] In Chapter 4, we referred to mental wellbeing instead of mental health.

explained by the countries' mobile internet accessibility. Multilevel analysis on data from 154,981 adolescents from 29 countries in the European region and Canada showed that in countries where relatively few adolescents reported intense SMU, intense users report higher levels of psychological complaints, lower levels of life satisfaction, and lower levels of family support than non-intense users. However, in countries where relatively many adolescents reported intense SMU, intense and non-intense users reported equal levels of psychological complaints, and intense users reported higher levels of life satisfaction and family support than non-intense users. In all countries, intense users reported higher levels of friend support than non-intense users, and this association became stronger as the countries' proportion of intense users increased. In some countries, intense users reported less school satisfaction and more schoolwork pressure than non-intense users, but this was not explained by the countries' proportion of intense users.

The association between problematic SMU and wellbeing was more robust than the one for intense SMU, because it was negative across all national contexts and this applied to all investigated indicators of wellbeing, although the strength of the negative associations varied across countries. The countries' mobile internet accessibility did not explain the observed country-level differences in intense or problematic SMU. Overall, the findings suggest that intense SMU could be beneficial as well as detrimental to wellbeing, depending on the country context and wellbeing domain, whereas problematic SMU consistently poses a risk for impairments in multiple wellbeing domains.

Most studies on the association between SMU behaviors and wellbeing are cross-sectional. Therefore, the next four chapters investigated the association between SMU intensity, SMU problems, and adolescent wellbeing in more detail using longitudinal data. Other than in Chapters 3 and 4, where SMU intensity was measured with the frequency of online communication, SMU intensity in the following chapters was indicated by the average frequency of diverse SMU activities, ranging from more active to more passive activities. **Chapter 5** investigated whether changes in ADHD-symptoms (i.e., attention deficits, impulsivity, hyperactivity), preceded or followed from changes in SMU intensity and SMU problems using three waves of data from 543 Dutch adolescents. Findings from random intercept cross-lagged panel modelling showed that within adolescents, increases in SMU problems predicted subsequent increases in ADHD-symptoms, in particular attention deficits and impulsivity (but not hyperactivity), with moderate to large effect sizes. Changes in SMU intensity did not predict subsequent changes in any ADHD-symptoms. Reversely, changes in ADHD-symptoms neither changed adolescents' level of SMU intensity nor SMU problems over time. Together, these findings suggest a unidirectional relation, whereby SMU problems, and not the intensity of SMU, affect adolescents' ADHD-symptoms.

Building on the previous chapter, **Chapter 6** investigated the direction of the association between SMU intensity, SMU problems, and depressive symptoms as well as life satisfaction, using three waves of data from 2,109 Dutch adolescents. Also, it investigated whether these associations were mediated by increased upward social comparisons, cybervictimization, worsened subjective school achievements, and fewer face-to-face contact with friends. Findings from random intercept cross-lagged panel models showed that, within adolescents, increases in SMU problems predicted subsequent decreases in life satisfaction and increases in depressive symptoms, with small effect sizes. Also, SMU problems increased upward social comparison and cybervictimization over time with small to moderate effect sizes. These changes, however, did not predict subsequent changes in depressive symptoms and life satisfaction, which suggests that upward social comparison and cybervictimization did not mediate the observed effect of SMU problems on these aspects of mental health. Reversely, changes in depressive symptoms and life satisfaction did not predict subsequent changes in SMU problems. Adolescents' SMU intensity was not associated with depressive symptoms and life satisfaction in any direction. Overall, in line with findings from Chapter 5, a unidirectional association was found between SMU problems and mental health.

Little is known about how SMU problems develop over time during adolescence. Using four waves of data from 1,419 adolescents, **Chapter 7** investigated how SMU problems developed over time and which wellbeing indicators predicted developments in SMU problems. In doing so, adolescents' trajectories of SMU problems were analyzed in parallel with their trajectories of SMU intensity[8] using latent class growth modelling. Four subgroups were

[8] In Chapter 7, we referred to SMU frequency instead of SMU intensity.

identified: two subgroups with relatively high levels of SMU problems over time, of which one reported high and one reported average levels of SMU intensity, and two subgroups with low levels of SMU problems over time, of which one reported low and one reported high levels of SMU intensity. In the two subgroups with high levels of SMU problems, the level of SMU problems remained high over time. The subgroup with low levels of SMU problems and high SMU intensity was the largest subgroup. Compared to this subgroup, adolescents in the two subgroups with high levels of SMU problems reported lower life satisfaction, but differed on other characteristics: The subgroup with high levels of SMU problems and high SMU intensity also showed more attention deficits and impulsivity, whereas the subgroup with high levels of SMU problems and average SMU intensity also showed poorer friendship competencies. Together, these findings highlight the emergence of different co-trajectories of SMU problems and SMU intensity throughout adolescence, depending on adolescents' psychosocial profile.

Chapters 3 until 7 highlighted the differences between SMU intensity and SMU problems in their associations with several indicators of wellbeing. However, to improve our understanding of the association between SMU and wellbeing, further scrutiny was desired. Therefore, **Chapter 8** investigated whether the association between SMU intensity and life satisfaction depended on (1) the type of SMU activity the adolescent engages in, (2) the (non)linear assumptions of the association, (3) individual characteristics, (4) whether SMU problems were considered, and (5) the level of analysis. Multilevel analyses on four waves of longitudinal data among 1,419 adolescents indicated that, at the within-person level, on average, changes in the intensity of any type of SMU activity were not associated with changes in life satisfaction, regardless of whether we controlled for changes in SMU problems. However, for some adolescents, increases in SMU intensity were associated with decreases in life satisfaction, whereas for others, increases in SMU intensity were associated with increases in life satisfaction. This individual variation could not be explained by adolescents' tendency to engage in upward social comparisons. At the between-person level, adolescents with higher averages in SMU intensity reported lower average levels of life satisfaction than adolescents with lower averages in SMU intensity, although this association was small in effect size, and disappeared when controlling for adolescents' average level of SMU problems. We did not find support for the proposition that different types of SMU activities have differential associations with wellbeing. Also, no evidence was found for curvilinear associations between the intensity of SMU activities and life satisfaction. In sum, results suggest that taking into account individual heterogeneity, considering SMU problems, and disentangling within- from between-person effects are important for understanding the relation between SMU intensity and wellbeing.

## Key Findings

### (1) The Social Media Disorder-Scale Is a Reliable and Valid Instrument to Measure Problematic SMU

There are concerns about adolescents who display problematic SMU (Griffiths & Kuss, 2017; Kuss & Billieux, 2017; Marino et al., 2018b). Therefore, it is essential that an instrument is available for research on problematic SMU that adequately reflects the theoretical conceptualization of problematic SMU and that this instrument is valid and reliable. Findings from Chapters 2 and 3 showed that the nine-item SMD-scale has good psychometric properties, both in the Netherlands as well as throughout the European region and Canada. Our findings suggest that the scale should be used as a unidimensional scale, including nine items which are all important indicators of problematic SMU. Also, researchers can use the scale to identify subgroups of users, including normative, at-risk, and problematic users. Furthermore, the scale can be used to reliably compare the prevalence of problematic SMU across countries and adolescent groups differing in gender, age, and socioeconomic status. These findings are an important step for providing researchers with a psychometrically sound instrument to measure problematic SMU, which is pivotal considering the possible detrimental effects of problematic SMU, as shown by our longitudinal findings (Chapters 5, 6, 8).

### (2) Rather Than the Intensity of SMU, Problematic SMU is Negatively Related to Wellbeing

Our cross-sectional as well as longitudinal studies showed that SMU problems were negatively related to multiple domains of adolescent wellbeing, including their mental health, school wellbeing, and social wellbeing, while higher SMU intensity was not or to a smaller extent (Chapters 4-6, 8). Furthermore, over time, increases in SMU intensity were not or barely related to subsequent increases in SMU problems and therefore, higher SMU intensity also did not deteriorate wellbeing indirectly through SMU problems (Chapters 5, 6). Together, these findings highlight the importance of considering SMU intensity and SMU problems as associated but different dimensions of SMU: although they are correlated (Chapters 3, 4, 7), they seem to differ with respect to their potential impact on wellbeing.

### (3) The Association Between Problematic SMU and Wellbeing is Independent of Country Context

Findings from Chapters 3 and 4 showed that problematic SMU is a global risk factor, because in all countries it was negatively associated with multiple domains of wellbeing. In contrast, the relation between SMU intensity and wellbeing was more country-context dependent, as positive as well as negative associations were found between higher SMU intensity and indicators of wellbeing across countries (Chapter 4). These findings suggest that the negative relation between problematic SMU and wellbeing is a robust finding and that, worldwide, problematic users face several risks related to wellbeing.

### (4) Lower Wellbeing Is a Predictor As Well As Outcome of SMU problems, Depending on the Analysis Strategy

Our longitudinal chapters investigating directionality showed a unidirectional association between SMU problems and indicators of wellbeing: Within adolescents, increases in SMU problems predicted subsequent increases in ADHD-symptoms and decreases in life satisfaction. Reversely, increases in ADHD-symptoms and decreases in life satisfaction did not predict subsequent increases in SMU problems (Chapters 5, 6). Nevertheless, we acknowledge that this unidirectional conclusion should be nuanced, because in these chapters we focused on the dynamic of within-person associations. In a subsequent analysis of the same longitudinal data, we focused on between-person differences in wellbeing and their associations with SMU problems over time (Chapter 7). In these analyses, we found that adolescents with higher average levels of ADHD-symptoms and lower average levels of life satisfaction were more likely to show higher levels of SMU problems over time than adolescents with lower average levels of ADHD symptoms and higher average levels of life satisfaction. Together, although changes in wellbeing *within adolescents* were not associated with subsequent changes in SMU problems within adolescents (Chapters 5, 6), adolescents with *lower wellbeing relative to other adolescents* were more likely to report higher levels of SMU problems over time (Chapter 7). Conceptually, these findings suggest that stable individual differences in adolescents' wellbeing at the between-person level affect their susceptibility to SMU problems, whereas temporal fluctuations in wellbeing at the within-person level are not predictive of SMU problems.

### (5) SMU Problems Are Persistent Over Time

Chapter 7 identified four trajectories of SMU problems, which were, in general, persistent over time. More specifically, two trajectories showed relatively high levels of SMU problems that remained high over time, suggesting that problematic SMU is not a behavior that desists naturally. In addition, two trajectories showed persistently low levels of SMU problems. These findings are consistent with the finding that, on average, adolescents did not show a linear change in SMU problems over time (Chapters 6 and 8).



### (6) The Association Between SMU Intensity and Wellbeing Can Be Positive or Negative, Depending on Individual Characteristics, Country Context, and Wellbeing Domain

Although our longitudinal study showed that higher SMU intensity was, on average, not associated with wellbeing (Chapters 5, 6, 8), in some cases higher SMU intensity was related to lower levels of wellbeing, in other cases it was related with higher levels of wellbeing, or it was not related to wellbeing at all. More specifically, for some adolescents, increases in SMU intensity were associated with increases in life satisfaction, whereas for others, increases in SMU intensity were associated with decreases in life satisfaction, although the study did not identify which individual characteristics explained these differences (Chapter 8).

Our findings also suggest that country contexts matters, given that countries where intense SMU was more common showed a positive association between high SMU intensity and wellbeing indicators, whereas countries where this was less common reported a negative association (Chapter 4). Additionally, the association between SMU intensity and wellbeing varied per wellbeing domain. High SMU intensity was consistently associated with higher friends support. Nevertheless, in some countries, high SMU intensity was negatively associated with other wellbeing domains, such as school satisfaction (Chapter 4). Furthermore, increases in SMU intensity were associated with concurrent increases in face-to-face contact with peers (Chapter 6). Together, these findings suggest that higher SMU intensity can be both beneficial or harmful to wellbeing, depending on individual characteristics, country context, and wellbeing domain.

# Implications of Our Findings

## Conceptual Implications

The finding that the SMD-scale was reliable and valid (Key finding 1; Chapters 2, 3) is an important step for the measurement of problematic SMU, because the SMD-scale may advance the conceptualization of problematic SMU. More specifically, while some other widely used scales only include the six core criteria of addiction, namely *salience* (i.e., *preoccupation*), *mood modification* (i.e., *escape*), *relapse* (i.e., *persistence*), *tolerance*, *withdrawal*, and *conflict* (Andreassen et al., 2012, 2016; Griffiths, 2005), the SMD-scale adds three additional criteria: *problems* in important life domains due to SMU, *displacement* of important activities by SMU, and *deception* by lying about the time spent on SMU. This conceptual extension is considered theoretically meaningful, because the items *problems* and *displacement* indicate whether the behavior (here: SMU) has harmful implications. As such, the assessment of harmful implications is more strongly reflected in the SMD-scale than in other scales that only cover the abovementioned six criteria. This is important, because many scholars agree that harmful implications as a direct consequence of the behavior in question is an essential characteristic of behavioral addictions (Billieux, King, et al., 2017; Brand et al., 2020; Kardefelt-Winther et al., 2017). Also, by adding the three items, the conceptualization of problematic SMU is more in line with the DSM-5 definitions of other (suggested) behavioral addictions, such as internet gaming disorder and gambling disorder (American Psychiatric Association, 2013). Thus, the nine-item SMD-scale is a more comprehensive conceptualization of problematic SMU, that is more in line with the scholarly and clinical definition of behavioral addictions.

The finding that higher levels of SMU problems were persistent (Key finding 5; Chapters 6-8), together with the finding that SMU problems were negatively related to multiple domains of wellbeing (Key finding 2; Chapters 4-6, 8), is important for the discussion on whether problematic SMU represents addictive behavior, as the SMD-scale intends. Although problematic SMU is measured with symptoms of addiction similar to substance addiction criteria, it has been argued that, despite such an operationalization, problematic SMU may not represent addiction (Kardefelt-Winther et al., 2017; Van Rooij & Prause, 2014). Several scholars stressed that two main criteria define behavioral addiction: First, the behavior in question leads to significant harm or distress and second, the behavior is persistent or recurs for a significant period of time (Billieux, King, et al., 2017; Billieux, Van Rooij, et al., 2017; Kardefelt-Winther et al., 2017). These criteria are also included in the criteria for recognized behavioral addictions, including gambling and gaming disorder, in the latest version of the International Classification of Diseases (ICD-11; World Health Organization, 2019). Scholars are concerned that those reporting addiction symptoms like substance addiction symptoms related to normative everyday activities, such as SMU, do not meet the aforementioned two key criteria of behavioral addiction. For example, *preoccupation* with social media may not interfere with daily life in the same way that preoccupation with substances does. Therefore, scholars emphasized that the application of substance use criteria to identify behavioral addictions may not be justified (Kardefelt-Winther et al., 2017). However, our findings challenge this criticism, because both our studies showed that adolescents with higher levels of SMU problems, as defined by substance addiction criteria, reported impaired wellbeing in several life domains (Chapters 4-6, 8). Furthermore, they continued to show high levels for a prolonged period of time (Chapter 7). Thereby, these findings support the idea that problematic SMU, as defined by substance addiction criteria, reflects addiction-like behavior.

Nevertheless, more research is essential to verify the suggestion that problematic SMU is a behavioral addition. Although we found that *moderate* levels of SMU problems were persistent over time (Chapter 7), future research exploring the course of *higher* levels of SMU problems is important to the question whether problematic SMU identifies addiction to social media. Furthermore, we would like to underline that our studies focused on young adolescents. More research testing whether SMU problems are persistent and hamper daily life during other life phases are important (e.g., during late adolescence and adulthood). Such studies may set out whether the persistent and harmful nature of SMU problems as found in our research are limited to early adolescence or emerge over the whole life course.

## Methodological Implications

The finding that the SMD-scale had good psychometric properties (Key finding 1; Chapters 2-3) implies that the scale is suited for research on problematic SMU. Researchers adopting the scale can use the scores on the scales in different ways. One strategy is to use adolescents' sum-score of the nine items, which is indicative of the number of present symptoms, that is, the level of SMU problems. Given the distribution of the scale's sum-score, (zero-inflated) Poisson regression techniques are required when studying the sum-score as an outcome (Atkins & Gallop, 2007). Another strategy is to divide adolescents' sum-scores into categories. Based on latent class analysis (Chapter 2), we identified three subgroups of users: normative (no symptoms or one symptom), at-risk (two to five symptoms), and problematic (six to nine symptoms). This operationalization allows researchers to compare subgroups of users on, for example, their wellbeing. In addition, it may be promising to study SMU problems as a latent variable. The advantage of using a latent variable is that it considers that some items contribute more to the underlying concept than other items, although the differences in the contributions of the SMD-scale items were, in general, small (Chapters 2 and 3). Furthermore, latent variables take into account the measurement error of the items, which is often a more realistic representation of the data (Bollen, 2002).

Also, the finding that rather than the intensity of SMU, SMU problems were negatively related with wellbeing (Key finding 2; Chapters 4-6, 8), together with the finding that these two SMU behaviors were correlated (Chapters 3, 4), is important for future research. More specifically, to improve our understanding of the association between adolescents' SMU intensity and wellbeing, it is pivotal that future studies consider SMU problems, by controlling for them, when studying the association between SMU intensity and wellbeing. This would limit the chance of finding a spurious negative association.

In addition, our findings illustrate the importance of using multiple analytical methods for longitudinal data to understand the association between SMU behaviors and wellbeing: Although random intercept cross-lagged panel models indicated that changes in wellbeing did not predict subsequent changes in SMU problems on the within-person level, this does not exclude the possibility that lower wellbeing at the between-person level affect adolescents' susceptibility to SMU problems, as demonstrated by our study using latent class growth modelling (Key finding 4; Chapter 5-7). That is, for example, while adolescents with higher levels of ADHD-symptoms compared to the average adolescent seemed sensitive to SMU problems (Chapter 7), adolescents' SMU problems did not vary as a function of their temporal fluctuations in ADHD-symptoms (Chapter 5). Other research also suggests that between-person differences in wellbeing impact SMU problems: A longitudinal study among adolescent girls that used latent growth modelling showed that girls with higher levels of depressive symptoms at baseline reported stronger increases in SMU problems over time than girls with lower levels of depressive symptoms at baseline (Raudsepp & Kais, 2019). Hence, relying solely on within-person fluctuations of behaviors, such as random intercept cross-lagged panel models, to derive the potential causal order of behaviors may not be justified, as this type of analysis does not establish the potential influence of more stable individual characteristics. In line with this suggestion, recently, other researchers stressed that the limitation of random intercept cross-lagged panel models is that it does not provide insight into the effects of between-person differences, while this is often relevant in research on psychology and individual development (Lüdtke & Robitzsch, 2021; Orth et al., 2021).

In addition, the finding that at the within-person level, temporal fluctuations in wellbeing were not associated with subsequent temporal fluctuations in SMU problems (Chapters 5, 6), should be interpreted in light of the yearly time intervals of our data. More specifically, the finding does not exclude the possibility that changes in wellbeing may induce changes in SMU problems within shorter time intervals (e.g., month, week, day). After all, the dynamic of behaviors is often dependent on the time scale used to capture the behaviors, which is also referred to as the *galloping horse fallacy*: A horse's movement at walking pace is not representative of its movement at galloping pace (Keijsers & Roekel, 2018). Taken together, to paint a more complete picture of the dynamics of the association between SMU behaviors and wellbeing, future longitudinal studies on this association may adopt complementary analytical strategies and study these dynamics within different time frames.

## Theoretical Implications

Adolescents' SMU has raised concerns among many (Unicef, 2017; Yardi & Bruckman, 2011). In line with these concerns, several studies showed a negative association between SMU and wellbeing (Frost & Rickwood, 2017; Kelly et al., 2018; Twenge, Martin, et al., 2018). Our finding that this negative relation rather applied to SMU problems, than the intensity of SMU (Key finding 2; Chapters 4-6, 8), nuances this line of research. Recently, several other longitudinal and systematic reviews showed no or only a very small negative average association between adolescents' SMU intensity and wellbeing (Coyne et al., 2020; George et al., 2020; Meier & Reinecke, 2020; Orben et al., 2019; Piteo & Ward, 2020). Researchers stressed that reports of negative associations were mostly found in cross-sectional work, were particularly representative of earlier decades of research, were driven by analytical decisions (e.g., control variables included), depended on the conceptualization of both SMU and wellbeing, and only applied to specific groups of individuals (Dienlin & Johannes, 2020; Odgers & Jensen, 2020; Orben, 2020a; Orben et al., 2019). Our findings add to this by suggesting that the negative associations between SMU intensity and wellbeing were possibly driven by SMU problems, given that two SMU behaviors were correlated and that the negative relation between the intensity of SMU and wellbeing was often not found (anymore) when taking into account SMU problems (Chapters 5, 6, and 8).

Researchers proposed that spending much time on social media threatens adolescents' wellbeing, for example, because it goes at the expense of meaningful activities (e.g., offline socializing with friends), or because it induces upward social comparisons due to the abundance of idealized self-portrayals of others on social media (Twenge, 2019; Underwood & Ehrenreich, 2017; Verduyn et al., 2020). However, our findings suggest that these adversities do not emerge simply by using social media intensively. The discourse that high screen time is an indicator of risky behavior may be obsolete nowadays, given that social media are omnipresent in adolescents' daily lives and intense SMU could be considered as rather normative (Anderson & Jiang, 2018; Smahel et al., 2020). Instead, adverse SMU effects seem to be driven by the unique characteristics of problematic SMU, such as having diminished control over thoughts, emotions, and behaviors due to SMU, or having conflicts with others due to SMU.

By contrast, adolescents engaging in higher SMU intensity (without SMU problems) may be well able to regulate their use and to combine it with important activities. Accordingly, our findings showed that intense users reported more friends support than non-intense users (Chapter 4), that increases in SMU intensity were associated with concurrent increases in face-to-face contact with friends (Chapter 6), and that subgroups of adolescents reporting high SMU intensity showed higher levels of friendship competencies than subgroups reporting lower and average SMU intensity (Chapter 7). Similarly, other researchers found that adolescents reporting daily SMU spent more time with friends in the evenings than those who did not report daily SMU (De Looze et al., 2019). Together, these findings challenge the *displacement hypothesis,* which postulates that SMU harms adolescents' wellbeing, because it goes at the expense of offline social interaction and the quality of friendships (Twenge, 2019; Twenge & Campbell, 2018; Underwood & Ehrenreich, 2017). Instead, in line with the *stimulation hypothesis* (Valkenburg & Peter, 2007, 2011), high SMU intensity may be an indicator of social involvement with peers, rather than impaired (social) wellbeing. After all, social media allow adolescents to maintain and strengthen friendships, for instance by facilitating sharing feelings or worries with friends (Valkenburg & Peter, 2009; Verduyn et al., 2017).

In addition, the finding that lower wellbeing (on the between-person level) predicted SMU problems (Key finding 4; Chapter 7) supports theory on the emergence of problematic internet-related behaviors. According to the *cognitive behavioral model*, pre-existing psychological problems drive certain maladaptive cognitions, such as the perception that engaging in the behavior of interest (here: SMU) mitigates one's sorrows or negative feelings. Such distorted thoughts may ultimately lead one to depend on the behavior in question. Building on this model, Caplan's model of problematic internet use postulates that individuals suffering from low mental health often perceive their social competencies as poor. Consequently, they may develop a preference for online social interaction over face-to-face encounters, because they believe that online their social vulnerabilities are less visible. This preference for online interaction may increase the risk of developing problematic internet-related behaviors (Caplan, 2003). However, these models do not explain why other mental health problems, in particular ADHD-symptoms, may increase adolescents' sensitivity to SMU problems (Chapter 7). To that end, research on ADHD and addictions could provide some directions. Researchers proposed that people with ADHD are sensitive to developing substance-related addictions, because they use substances for self-medication, for example, because substances calm their restless thoughts (Lambert & Hartsough, 1998; Ohlmeier et al., 2008; Wilens, 2004). Also, ADHD is associated with novelty seeking and longing for external stimuli, which, in turn, could be satisfied with substance abuse (Ballon et al., 2015). Furthermore, adolescents with ADHD may be sensitive to substance addiction because due to their impulsivity they typically lack the self-control to resist impulses to satisfy short-term needs, such as the uplifting effects of substances (Rømer Thomsen et al., 2018). In the same way, adolescents with ADHD-symptoms may be more likely to become dependent on social media to cope with their symptoms, to satisfy their recurring need for entertainment, and/or because of their limited ability to resist impulses to use social media.

Extending these theoretical mechanisms, SMU problems may, furthermore, exacerbate the psychological vulnerabilities that could make adolescents sensitive to SMU problems. In our studies, lower mental health was a predictor as well as outcome of SMU problems (Key finding 4; Chapters 5-7). This suggests a downwards spiral of lower mental health, whereby psychologically vulnerable adolescents are more likely to develop SMU problems, which, in turn, strengthens their vulnerabilities. However, our findings suggest that the observed negative effect of SMU problems on mental health did not exclusively affect adolescents with lower mental health. In fact, the observed associations from random intercept cross-lagged panel models imply that SMU problems predicted subsequent lower mental health, regardless of adolescents' stable level of mental health. This means that SMU problems may exacerbate pre-existing psychological vulnerabilities, but also pose a risk to the mental health of adolescents who do not show such vulnerabilities.

Next, the finding that the association between SMU intensity and wellbeing depended on individual as well as country factors (Key finding 6; Chapters 4, 8) supports the *differential susceptibility to media effects model* (Valkenburg & Peter, 2013). This theoretical model posits that media effects are contingent on dispositional factors, such as gender, personality, and moral values, as well as social factors that are context-related, such as the cultural norms and habits within a society (Valkenburg & Peter, 2013). According to our findings, a social factor that influenced the association between SMU intensity and wellbeing was the extent to which intense SMU was the norm within the adolescent population. Applying the *normalization thesis*, this may be because once risk behaviors become normalized within the adolescent population, these behaviors may represent adolescents without problematic profiles, or even well-adjusted adolescents (Haskuka et al., 2018; Pennay & Measham, 2016; Sznitman et al., 2015). As such, when high SMU intensity is normalized among adolescents within the society, intense users may represent mainstream adolescents, whereas in societies where high SMU intensity is rather exceptional, intense users may be more vulnerable adolescents. Other research also found that the association between SMU intensity and wellbeing depended on the social context (O'Leary & Volkmer, 2021).

A theoretical suggestion that was not supported by our findings was the *active versus passive SMU hypothesis* (Chapter 8). According to this suggestion, *active* SMU, which involves sharing content and communication with others on social media, increases one's social capital and sense of belonging, thereby enhancing wellbeing. In contrast, *passive* SMU, which refers to viewing other people's messages or photos on social media that are typically biased toward positivity, induces feelings of envy, in turn, decreasing wellbeing (Dienlin & Johannes, 2020; Verduyn et al., 2017). Recent experience sampling studies also failed to find support for this hypothesis (Beyens, Pouwels, Van Driel, et al., 2020; Jensen et al., 2019; Valkenburg, Beyens, et al., 2021). As a result of these findings, it has been proposed to “abandon the active-passive dichotomy” in research on social media effects (Valkenburg, Van Driel, et al., 2021). A passive/active dichotomy may not be appropriate, because some SMU activities have passive as well as active characteristics. For example, *liking* messages, photos, or videos on social media implies a form of communication and could therefore be considered as active SMU. However, liking could also be regarded as passive SMU because it requires only one click and does not contribute to a dialogue. Also, reading received direct messages from peers via instant messengers could be considered as passive SMU, as it concerns viewing, but it also has an active component because it involves social interaction with others. Therefore, it is complex to classify SMU activities as either passive or active, and consequently, to study their differential impact on wellbeing. Furthermore, effects of active and passive SMU are plausibly difficult to disentangle, given that active and passive SMU activities are highly intertwined: For example, responding to a photo or video on social media, which is considered as active SMU, requires viewing it first, which is considered as passive SMU. As such, disentangling the effects of time spent on active and passive SMU activities may not be feasible. Instead, research focusing on the content adolescents are exposed to (e.g., uplifting versus agitating) and how they experience this content may contribute more in understanding the relation between SMU and adolescent wellbeing (Griffioen et al., 2021; Valkenburg, Van Driel, et al., 2021).

## Practical Implications

Although more research replicating our findings in other samples is necessary, focusing on the absolute levels, the course, and negative consequences of SMU problems among adolescents, the aforementioned theoretical implications may provide some directions for practice. The finding that not the intensity of SMU, but SMU problems were related to lower wellbeing (Key finding 2; Chapters 4-6, 8), informs parents and teachers who are concerned about adolescents’ engagement with SMU. More specifically, our findings suggest that, nowadays, high intensity of SMU may be best understood as a normative behavior that serves important functions contributing to adolescents’ development (Chapter 4). After all, social media allow adolescents to connect with their peers, share their narratives, and express their social identity, which are of crucial importance for their individual development and everyday functioning (Granic et al., 2020; O'Keeffe et al., 2011; Valkenburg & Peter, 2011). As such, problematizing SMU in general may hinder the understanding of the daily lives of today's adolescents. In qualitative studies on adolescents' experiences with their SMU or smartphone use, adolescents reported that they were disappointed that parents and/or teachers primarily expressed their concerns about their screen time instead of trying to understand the importance of SMU in their daily lives (Hjetland et al., 2021; Jameel et al., 2019; O'Reilly, 2020). Nevertheless, it may be important for adolescents and those concerned with their wellbeing to be aware that adolescents' SMU may become problematic. This is the case when, for example, adolescents experience diminished ability to stop and control SMU, or when SMU is constantly on top of their mind. Especially these behaviors, and not the time spent on or frequency of SMU, may have detrimental effects related to adolescent wellbeing.

Given that SMU problems were negatively related to multiple domains of adolescent wellbeing, that this was found across many countries, and that SMU problems were persistent over time (Key findings 2, 3, and 5; Chapters 4-8), schools and/or (government) institutions may consider developing programs aimed at preventing and reducing SMU problems among adolescents. Although the proportion of adolescents reporting problematic SMU (i.e., reporting six to nine symptoms) was low (Chapters 2, 3), such programs may still be relevant, as Chapter 2 showed that about one third of Dutch adolescents reported at-risk SMU (i.e., reporting two to five symptoms). Not only problematic users, but also at-risk users were more likely to experience problems on several important life domains than normative users (i.e., reporting no symptoms or one symptom) (Chapter 2). Researchers using the SMD-scale to study the same three subgroups among a nationally representative sample of Finnish adolescents, showed that, consistent with our findings, at-risk users were more likely to report health complaints, low self-rated health, loneliness, and sleep problems than normative users (Paakkari et al., 2021). Furthermore, our longitudinal study showed that adolescents' increases in SMU problems predicted subsequent decreases in mental health, regardless of their absolute level of SMU problems (Chapters 5, 6). Together, these findings may warrant the development of prevention and intervention programs on SMU problems among adolescents.

To that end, programs providing adolescents with insight into their SMU behaviors may be valuable, focusing on making adolescents aware of whether their SMU is problematic, which is considered an essential starting point to change behaviors (Throuvala et al., 2020). For example, researchers from the Netherlands have recently launched a website aimed at providing people with insight into their media use and promoting a 'digital balance'. The program on the website does not target screen time, but whether digital media use interferes with important life domains including physical exercise, sleep, mental health, and social activities (Trimbos-institute, 2020). Such programs may help adolescents to become aware of their (problematic) attachment to social media, which may be relevant even at an early age: Research among Dutch early adolescents showed that the majority of the 10- and 11-year-olds already use social media, and that 11-year-olds in elementary schools sometimes already report problematic SMU (Boer & Van den Eijnden, 2018; Kennisnet, 2017).

In addition, programs focusing on preventing and reducing SMU problems may be considered. In developing such programs, abstaining from social media to prevent or overcome SMU problems may not be an effective strategy. This is because some activities that are relevant to adolescents' social and educational development take place via social media, such as socializing with peers and communication about schoolwork with teachers and classmates (Smahel et al., 2020; Underwood & Ehrenreich, 2017). Therefore, withdrawing from social media (i.e., 'digital detox') could go at the expense of important life domains that are crucial to adolescents' wellbeing and psychosocial functioning, and could possibly even lead to social exclusion. Alternatively, programs could focus on supporting adolescents in keeping or regaining control over their SMU. Experimental research among university students in the United Kingdom showed that students engaging in *mindfulness* exercises for ten consecutive days reported a decrease in SMU problems, whereas students not engaging in mindfulness did not report a change in SMU problems (Throuvala et al., 2020). Mindfulness, that is, the ability to be conscious about experiences in the present and to dissociate from automatic and recurring thoughts and behaviors, supports coping with distractions, which could possibly help adolescents to overcome their SMU problems (Du et al., 2021; Throuvala et al., 2020). In addition, interventions based on strengthening *motivation to change, self-efficacy* (Michie et al., 2011) and *implementation intentions* (Gollwitzer & Sheeran, 2006) may also be helpful. For example, preliminary findings on the effectiveness of an intervention aimed at raising awareness and enhancing control over smartphone use among Dutch university students showed that students' level of problematic smartphone use was reduced when they had formulated implementation intentions to use their smartphone more consciously (e.g., leave the smartphone outside of the bedroom to resist temptation to use the smartphone in bed) (Schiltkamp, 2021).

We stress that some adolescents may display SMU problems because of, for example, poor mental health (Key finding 4; Chapter 7). These adolescents may be more sensitive to SMU problems, because SMU possibly relieves their sorrows or calms their restless thoughts, in other words, SMU may help them to escape from or to cope with their problems (Davis, 2001; Kuss & Griffiths, 2011, 2017). As such, SMU problems may be a symptom of underlying vulnerability. Therefore, problematic users may benefit from individual support from, for example, a (school) counsellor or psychologist, who addresses the source of their problematic attachment to SMU.



## Future Directions

Alongside the abovementioned implications, this dissertation opens avenues for several new research directions. We divided these directions into four categories, which we outline below.

### Extending Knowledge on the Clinical Relevance of Problematic SMU

In the past few years, many scholars have questioned whether problematic SMU is clinically relevant (Brand et al., 2020; Kardefelt-Winther et al., 2017; Starcevic et al., 2018). To answer this, it should be determined whether the behavior constitutes a behavioral addiction. Although our findings suggest that problematic SMU, as measured by the SMD-scale, represents addiction-like behavior, above we stressed that more research on the development and consequences of SMU problems throughout different developmental periods is essential to consolidate this suggestion. Furthermore, data other than self-reports are important to establish whether problematic SMU reflects addictive behavior. To that end, assessments from psychologists or addiction care professionals on whether adolescents reporting problematic SMU (i.e., six to nine symptoms on the SMD-scale) meet the criteria for a behavioral addiction are considered valuable (Billieux, Van Rooij, et al., 2017; Kardefelt-Winther et al., 2017). However, such a validation is complex, as there are no diagnostic criteria available that professionals can use as a 'golden standard', given the absence of a clinical recognition of problematic SMU in any diagnostic handbook. As a possible strategy, addiction care professionals could conduct diagnostic interviews based on the criteria for recognized behavioral addictions, such as gaming disorder based on the ICD-11 (World Health Organization, 2019), but then applied to SMU. According to these criteria, a gaming disorder is characterized by impaired control over gaming, prioritizing gaming over other interests and daily activities, significant distress or impairment in daily life functioning due to the gaming behavior, and continuation of gaming despite negative consequences, for a period of typically 12 months (World Health Organization, 2019). When the professional's assessment of problematic SMU based on ICD-11 gaming criteria and an assessment based on the SMD-scale identify the same adolescents as problematic users, then this could support the suggestion that problematic SMU, as measured by the SMD-scale, reflects a behavioral addiction. Furthermore, it implies that the SMD-scale could be used for the purpose of screening adolescents for problematic SMU.

Additional research on the nature of problematic SMU is crucial, because if more research suggests that problematic SMU should be understood as addictive behavior, then the behavior can possibly be recognized as such in a diagnostic manual as a mental disorder. Such an inclusion would facilitate professional help to problematic users of social media, because in many countries, treatments will only be reimbursed if the behavior is recognized in an official diagnostic classification system (Kuss & Billieux, 2017; Van den Brink, 2017). However, it is conceivable that the relevance of including problematic SMU as social media addiction in a diagnostic manual may change in future decades, given the rapidly changing online environments. Furthermore, diagnostic recognition of problematic SMU may raise the question whether other potential internet-related addictive behaviors, such as smartphone addiction, also require a separate diagnostic category. It may be undesirable to consider diagnostic recognition for each candidate addictive behavior. Therefore, should a diagnostic recognition of addiction-like SMU be warranted, including a more general diagnostic classification, such as 'Internet-related addiction', may be more tenable.

## Extending Theoretical Knowledge on Problematic SMU

So far, little is known about individual differences in the effect of SMU problems. Multilevel modelling techniques applied to longitudinal data allow to explore this so-called *heterogeneity*. In our longitudinal chapters, we did not investigate heterogeneity for the within-person association between SMU problems and wellbeing (Chapters 5, 6, 8). Instead, we assumed that the association was homogeneous (i.e., the same across adolescents), while in psychology, person-specific heterogeneity in associations is often more realistic (Keijsers & Roekel, 2018). Accordingly, our findings (Chapter 8), as well as earlier experience sampling studies (Beyens, Pouwels, Valkenburg, et al., 2020; Beyens, Pouwels, Van Driel, et al., 2020; Valkenburg, Beyens, et al., 2021), demonstrated that the within-person association between adolescents' SMU intensity and wellbeing differed substantially across adolescents. For example, one study showed that, while on average momentary passive SMU was not associated with momentary changes in wellbeing, for 46% of adolescents passive SMU increased wellbeing, for 10% passive SMU decreased wellbeing, and for 44% there was no association (Beyens, Pouwels, Valkenburg, et al., 2020). Future longitudinal studies adopting multilevel analytical techniques to study individual variation in within-person associations between SMU problems and wellbeing provide more knowledge on the robustness of the association across adolescents. Furthermore, with intensive longitudinal data (e.g., 100 measurements per adolescent), more advanced multilevel techniques, such as dynamic structural equation modelling (Asparouhov et al., 2017), allow researchers to study heterogeneity in the effect of SMU problems on wellbeing and vice versa in one model (Beyens, Pouwels, Van Driel, et al., 2020; Valkenburg, Beyens, et al., 2021; Valkenburg, Pouwels, et al., 2021).

Not only does the association between SMU problems and wellbeing possibly differ across adolescents, it may also differ across time frames. Chapter 6 yielded rather small effect sizes for the effects of SMU problems on, for example, depressive symptoms one year later. Although these lagged effects were small, findings showed that at the first measurement occasion, increases in SMU problems co-occurred with moderate increases in depressive symptoms (Chapter 6). Together, these findings imply that, although the effects of SMU problems on these outcomes one year later were small, there may have been a stronger effect that diminished over time. In other words, SMU problems may impact wellbeing more in the immediate period following increases in SMU problems than one year after increases in SMU problems. In line with this suggestion, it has been argued that digital media use has stronger short-term effects than long-term effects on wellbeing (Dienlin & Johannes, 2020), which relates to the galloping horse fallacy mentioned earlier (Keijsers & Roekel, 2018). To gain more insight into short-term effects of SMU problems, the use of more intensive longitudinal data, such as weekly or monthly measures, is important. Also, the use of experience sampling studies, repeated for several times a year, is considered promising. Through experience sampling, participants report on their thoughts and behaviors several times a day for a short period (e.g., one week), typically through smartphones, which allows researchers to study momentary associations (Beyens, Pouwels, Valkenburg, et al., 2020; Valkenburg, Pouwels, et al., 2021). By repeating experience sampling data collection on SMU problems multiple times per year, it is possible to study the differences between short- and long-term effects, thereby improving the understanding of the effect of SMU problems.

The use of more intensive longitudinal data may also enhance current knowledge on the development of SMU problems. In particular, this may allow researchers to capture adolescents' transitions from normative to at-risk SMU, from at-risk to problematic SMU, as well as the reverse. Our findings showed that adolescents' levels of SMU problems were rather persistent throughout four years (Chapter 7). Again, this should be interpreted in light of the yearly time intervals that were used for the assessments. There may have been unobserved fluctuations in SMU problems in between the yearly assessments. Furthermore, longitudinal research investigating factors that accelerate adolescents' transitions from normative to at-risk SMU, and from at-risk to problematic SMU, deepen our understanding of the development of SMU problems. Research on these transitions is considered important, because the higher the level of SMU problems, the higher the risk of experiencing problems related to mental health, school, and sleep (Chapter 2).

Another important direction for future research is to study the possible mechanisms explaining our effects. For example, the association between SMU problems and subsequent increases in ADHD-symptoms (Chapter 5) is possibly indirect: Problematic users may experience stress or anxiety when it is not possible to access their smartphone, also referred to as *nomophobia* (Kuss & Griffiths, 2017). This stress or anxiety may harm their ability to sustain attention on offline activities, particularly when SMU is not possible. Also, the association between low life satisfaction and SMU problems over time (Chapter 7) is in line with theoretical models proposing that psychosocial vulnerabilities cause problematic internet-related behaviors (Caplan, 2003; Davis, 2001). However, these models describe that the relation is indirect, driven by *maladaptive cognitions* about social media (e.g., the perception to only have a meaningful life on social media), as well as by a *preference for online interaction* over face-to-face-communication. To better understand our findings, more research focusing on such mediating factors is important.

This dissertation highlights the outcomes of SMU problems more extensively than the predictors. Therefore, more research on the causes of SMU problems is desired. To do so, the use of longitudinal data from childhood onwards until late adolescence is crucial, because SMU problems may emerge at a young age (Chapter 7). Establishing the onset of SMU problems could improve estimating the causal effect of specific psychosocial vulnerabilities on developing SMU problems, because this allows to exclude the possibility that the respective psychosocial vulnerabilities are the result of earlier SMU problems. Furthermore, in future longitudinal studies on the origins of SMU problems, it is important to not only focus in psychosocial vulnerabilities, such as poor mental health or social skills, but also on genetic factors (Brand et al., 2019), as well as personality characteristics, such as extraversion (Lee et al., 2017; Sun & Zhang, 2021). Contextual factors, such as the family, peer, school, and country context, also likely play a role in adolescents' susceptibility to SMU problems. For example, our findings showed large country differences in problematic SMU (Chapter 4), suggesting that the country context affects this risk. Overall, longitudinal research on SMU problems from childhood onwards examining the role of individual as well as contextual factors on the onset of SMU problems, are expected to provide more insight into the causes of SMU problems.

## Testing Interventions or Strategies to Prevent and Overcome Problematic SMU

Research testing the effectiveness of prevention and intervention programs focusing on how SMU problems can be prevented or reduced is scarce. This is understandable, because knowledge on the impact of SMU problems is limited. The development of programs on SMU problems is particularly valuable when the detrimental nature of SMU problems has been empirically established. Our longitudinal study addressed this gap and suggested that SMU problems impair adolescents' wellbeing (Chapter 5, 6), providing a first indication that the development of such programs may be warranted. As discussed earlier, programs focusing on promoting a digital balance (Trimbos-institute, 2020), mindfulness (Du et al., 2021; Throuvala et al., 2020), and implementation intentions (Gollwitzer & Sheeran, 2006; Schiltkamp, 2021), may be valuable in preventing or reducing SMU problems, yet their effectiveness for young adolescents have not been established empirically.

Also, there may also be a corporate responsibility of social media developers to prevent or reduce SMU problems. The popular film-documentary *The Social Dilemma* emphasized that social media are designed to make its users addicted, because they are full of incentives to want to use them more and more (Rhodes & Orlowski, 2020). For example, Snapchat attaches *streaks* to contacts, which display the number of consecutive days two people have sent *Snaps* (i.e., a photo or video that is visible for a maximum of 10 seconds) to each other. Long streaks typically symbolize close friendships and therefore, it may be important for young people to maintain or enhance their streaks by keep sending Snaps. In addition, Instagram users can see how many times their uploaded photo or video have been viewed by others, and furthermore, through the *like*-function, they can also see how many people explicitly appreciated their uploaded content. As such, users may be inclined to repeatedly return to Instagram to check for views and likes of their uploads. Changing or removing such incentives that may reinforce recurring visits may decrease the risk of developing SMU problems. For example, since this year (2021), Instagram allows its users to hide the number of views and likes under a photo or video they uploaded. Experimental research testing the effect of such changes on preventing or reducing SMU problems is considered promising.

## Identifying (Adolescents Engaging in) Healthy and Unhealthy SMU

A recurring question among scholars as well as parents, teachers, and policymakers, is what constitutes 'unhealthy SMU', that is, harmful SMU (Griffiths & Kuss, 2011; Orben, 2020b). For example, several studies have attempted to answer the question how much screen time is detrimental to adolescents (Przybylski & Weinstein, 2017; Twenge, Martin, et al., 2018). However, as discussed earlier, unhealthy media behaviors may be indicated by SMU problems, rather than by adolescents' intensity of SMU (Key finding 2, Chapters 4-6, 8). Other SMU dimensions that are considered unhealthy are, for example, becoming a victim of online bullying or sexual harassment, as well as exposure to fake news, complot theories, and promotion of dangerous behaviors, such as eating disorders and self-mutilation (O'Keeffe et al., 2011; Underwood & Ehrenreich, 2017; Valkenburg & Peter, 2011; Van Huijstee et al., 2021). Adolescents who use social media intensively may not necessarily be involved in such adverse online behaviors. For example, our findings showed that, while controlling for SMU problems, increased SMU intensity was not associated with increased cybervictimization one year later (Chapter 6).

Social media also facilitate activities that could be favorable to adolescents. As mentioned earlier, social media allow adolescents to form, maintain, and enhance new or existing friendships (Valkenburg & Peter, 2011; Verduyn et al., 2017). Furthermore, adolescents can experience entertainment on social media, for example by viewing uplifting videos with humorous content (Valkenburg, Van Driel, et al., 2021). In addition, social media allow adolescents to disclose their personal narratives and to receive feedback on these from peers, which are important for their individual development during adolescence (Granic et al., 2020; Valkenburg & Peter, 2011).

To gain more insight into healthy as well as unhealthy SMU, it would be particularly valuable for future research to explore (the prevalence of) patterns of specific beneficial as well as harmful online experiences as outlined above, instead of focusing the intensity of SMU activities (i.e., 'screen time'). A next step could be to investigate which individual characteristics reinforce these particular patterns of positive and negative online experiences, thereby identifying adolescents engaging in healthy and unhealthy SMU.

## Strengths and Limitations

A main strength of this dissertation is the use of nationally representative and internationally comparative cross-sectional data as well as longitudinal data. These different samples point towards comparable conclusions, namely that problematic SMU, and often not high SMU intensity, is detrimental to wellbeing, supporting the robustness of our conclusions. Also, the use of a variety of analytical methods allowed us to examine the psychometric properties of the SMD-scale in detail and to shed light on the association between SMU behaviors and wellbeing in different ways.

The studies in this dissertation also have limitations, of which some have already been acknowledged above. First, findings of the longitudinal studies should be interpreted in light of the yearly time intervals that were used in the data collection. The observed dynamics between SMU behaviors and wellbeing may be different when collecting data in shorter time intervals, as effects are likely contingent on the time intervals used to study associations (Keijsers & Roekel, 2018). Second, in our studies, we focused on particularly early and middle adolescents from 11 to 16 years old. The results of our studies may not be generalized to, for example, older adolescents, as the effects may be specific to the developmental period that we studied. Third, the conclusions from our longitudinal chapters are based on the same sample of Dutch adolescents (Chapters 5-8). Replication in other (inter)national samples is necessary to investigate the robustness and of our findings and generalizability to adolescents in other national contexts. After all, our study shows that SMU effects are sensitive to country contexts (Chapter 4). Fourth, the studies in this dissertation relied on self-report measures. The use of such measures to indicate SMU intensity is controversial, as adolescents may over- or underestimate their use because it may be difficult to recall their frequency of use (Junco, 2013; Parry et al., 2020). More objective measurements of SMU intensity, such as tracked time spent on particular SMU activities via smartphone apps, overcome the limitation of recall bias. However, many available time tracking facilities have practical challenges in recording time spent on (social media) applications and not always guarantee protection of private data. Furthermore, the knowledge of being tracked may influence usage behaviors of adolescents. As highlighted above, to understand the possible effects of SMU, it may be more informative for future research to focus on specific positive and negative experiences on or related to social media (e.g., social interaction with peers, encountered online content, SMU problems), instead of on improving the measurement of and testing the effect of tracked SMU activities on wellbeing. After all, time spent on SMU is not an indicator of adolescents' online experiences (Griffioen et al., 2021).

Fifth, we used different conceptualizations of SMU intensity in our studies. In our cross-sectional study (Chapters 3, 4), SMU intensity was indicated by the frequency of online communication on social media, which is a more active SMU activity because it involves social interaction. In our longitudinal study (Chapters 5-7), SMU intensity was a composite measure of different SMU activities, such as direct messaging with peers as well as browsing social network sites. As such, conclusions about the associations with SMU intensity should be interpreted in light of the respective operationalizations. However, it should be mentioned that the consequences of using different operationalizations of SMU intensity may be limited, given that our findings suggested that different SMU activities, ranging from active to more passive, do not yield different associations with wellbeing (Chapter 8), which was also supported by other researchers (Valkenburg, Van Driel, et al., 2021). Furthermore, with both operationalizations of SMU intensity, we observed comparable results, whereby rather problematic SMU related negatively to wellbeing than the intensity of SMU.



## Conclusion

This dissertation highlights the differences between two SMU behaviors, namely the intensity of SMU, indicated by the frequency of SMU, and SMU problems, indicated by addiction symptoms related to social media. This distinction is important for understanding the relation between SMU and adolescent wellbeing, because, in general, not the intensity of SMU, but SMU problems were negatively related to wellbeing. This finding informs those concerned with the wellbeing of adolescents that rather SMU problems are an indication of harmful SMU than high intensity of SMU. High intensity of SMU may be considered as normative adolescent behavior that often contributes to adolescents' involvement with their social environment. Given that our studies suggest that SMU problems are negatively associated with several wellbeing domains, and that SMU problems tend to be persistent over time, developing prevention and intervention strategies to reduce or overcome SMU problems may be warranted. However, more research replicating our findings is important to substantiate the need for such strategies. To that end, our findings suggest that the SMD-scale is suited for future research on adolescent problematic SMU. To extend current knowledge on problematic SMU, research focusing on the clinical relevance and individual susceptibility to (the harmful effects of) problematic SMU, as well as the theoretical mechanisms underlying the negative association between problematic SMU and wellbeing, are considered promising.

# Samenvatting

[SUMMARY IN DUTCH]

# Samenvatting

De populariteit van sociale media, oftewel sociale netwerk sites (bijv. Instagram en Facebook) en instant messengers (bijv. SnapChat en WhatsApp) is in de afgelopen jaren sterk toegenomen onder adolescenten (Anderson & Jiang, 2018; Lenhart et al., 2015). Sociale media spelen een steeds belangrijkere rol in het dagelijks leven van adolescenten, bijvoorbeeld in het contact met leeftijdgenoten en om eigen gebeurtenissen te delen (Granic et al., 2020; Valkenburg & Peter, 2011). Er zijn echter zorgen over de schadelijkheid van socialemediagebruik, bijvoorbeeld op het gebied van het welbevinden van adolescenten (Twenge, 2019; Underwood & Ehrenreich, 2017; Unicef, 2017). Adolescenten zouden bijvoorbeeld verslaafd kunnen raken aan sociale media, met aanzienlijke gevolgen voor hun mentale gezondheid (Griffiths & Kuss, 2017; Marino et al., 2018b). In dit proefschrift spreken we van *problematisch socialemediagebruik* wanneer er symptomen zijn van verslaving met betrekking tot socialemediagebruik (Lee et al., 2017). We gebruiken de term 'verslaving' niet in dit proefschrift, omdat sociale media verslaving niet als zodanig erkend wordt in psychologische handboeken (American Psychiatric Association, 2013; World Health Organization, 2019). Voorbeelden van kenmerken van problematisch socialemediagebruik zijn het ervaren van stress of angst wanneer het niet mogelijk is om sociale media te gebruiken (*ontwenningsverschijnselen*) of het continue denken aan sociale media, ook in offline situaties (*preoccupatie*). Problematisch socialemediagebruik wordt dus gemeten aan de hand van kenmerken van verslaving en niet door middel van de *intensiteit van socialemediagebruik,* zoals de tijd besteed aan socialemediagebruik per dag. Alhoewel veel adolescenten intensief gebruikmaken van sociale media, komen hoge niveaus van problematisch socialemediagebruik relatief weinig voor (Cheng et al., 2021; Inchley et al., 2020b). In dit proefschrift worden de intensiteit van socialemediagebruik en problematisch gebruik van sociale media daarom als twee verschillende dimensies beschouwd.

Er is nog weinig bekend over de mate waarin een hoge intensiteit en problematisch gebruik van sociale media schadelijk zijn voor het welbevinden van adolescenten, bijvoorbeeld voor hun mentale gezondheid. De vraag die in dit proefschrift centraal staat is in hoeverre beide dimensies van socialemediagebruik samengaan met een verminderd welbevinden bij adolescenten. Om deze vraag te beantwoorden, hebben we allereerst de kwaliteit van een instrument om problematisch socialemediagebruik te meten, namelijk de Social Media Disorder (SMD)-schaal (Van den Eijnden et al., 2016), onderzocht bij zowel Nederlandse als Europese en Canadese adolescenten (Hoofdstukken 2 en 3). Hiervoor hebben we gebruik gemaakt van nationale en internationale data van het Health Behaviour in School-aged Children (HBSC) onderzoek (Inchley et al., 2020b; Stevens et al., 2018). De SMD-schaal bestaat uit negen items die negen symptomen van verslaving meten, welke overeenkomen met de symptomen van gameverslaving zoals geformuleerd in de Diagnostic and Statistical Manual of Mental Disorders (American Psychiatric Association, 2013; Lemmens et al., 2015). Vervolgens hebben we op basis van HBSC-data onderzocht in hoeverre intensief en problematisch socialemediagebruik beide samenhangen met welbevinden en of deze relaties verschillen tussen landen (Hoofdstuk 4). Hierbij onderscheidden we verschillende domeinen van welbevinden, namelijk mentale gezondheid (bijv. levenstevredenheid), sociaal welbevinden (bijv. ervaren steun van vrienden) en welbevinden op school (bijv. ervaren schooldruk).

Om de relatie tussen socialemediagebruik en welbevinden nauwkeuriger te onderzoeken, hebben we in de daaropvolgende vier hoofdstukken gebruik gemaakt van data van Nederlandse adolescenten die gedurende een periode van vijf jaar meerdere keren hebben meegedaan aan het Digital Youth (DiYo) project van de Universiteit Utrecht (Van den Eijnden et al., 2018). Om zicht te krijgen op de richting van de verbanden tussen socialemediagebruik en welbevinden, zijn we nagegaan of een daling in welbevinden voorafging aan of volgde op een toename in de intensiteit van socialemediagebruik of problematisch socialemediagebruik *binnen* een adolescent. Hierbij werd een onderscheid gemaakt tussen verschillende indicatoren van mentale gezondheid, namelijk ADHD-symptomen (Hoofdstuk 5), levenstevredenheid (Hoofdstuk 6) en symptomen van depressie (Hoofdstuk 6). Bovendien hebben we bestudeerd of de gevonden afname in mentale gezondheid verklaard kan worden door cyberpesten, opwaartse sociale vergelijkingen, verminderd offline contact met vrienden en dalende schoolprestaties ten gevolge van problematisch socialemediagebruik (Hoofdstuk 6). Daarna hebben we onderzocht hoe problematisch socialemediagebruik en de intensiteit van socialemediagebruik zich in relatie tot elkaar ontwikkelden over tijd en welke domeinen van welbevinden samenhingen met deze ontwikkelingen (Hoofdstuk 7). Ook hier onderscheidden we verschillende domeinen van welbevinden: mentale gezondheid (namelijk levenstevredenheid, zelfvertrouwen en ADHD-symptomen) en sociaal welbevinden (namelijk vriendschap competenties). Vervolgens hebben we onderzocht of de relatie tussen de intensiteit van socialemediagebruik en welbevinden afhankelijk was van verschillende theoretische en methodologische factoren (Hoofdstuk 8). Voorbeelden van factoren zijn bijvoorbeeld of er *actief* (bijv. zelf iets posten op sociale media) of *passief* (bijv. scrollen door andermans profielpagina op sociale media) gebruik wordt gemaakt van sociale media, of de statistische methode waarmee relaties worden bestudeerd. Met deze hoofdstukken beogen we meer inzicht te geven in de relatie tussen socialemediagebruik en welbevinden bij adolescenten.

## Onderzoeksdata

De resultaten van de Hoofdstukken 2 tot en met 4 zijn gebaseerd op nationale en internationale cross-sectionele data van een representatieve groep adolescenten tussen de 11 en 16 jaar oud die deelnamen aan het Health Behaviour in School-aged Children (HBSC) onderzoek in 2017 en 2018 (Inchley et al., 2020b; Stevens et al., 2018). Het HBSC onderzoek wordt sinds 1983 elke vier jaar uitgevoerd in samenwerking met de World Health Organization (WHO). Het doel van het HBSC onderzoek is het monitoren van de gezondheid, het gezondheidsgedrag en het welbevinden van adolescenten op basis van vragenlijsten die adolescenten zelf invullen. Hoofdstukken 5 tot en met 8 zijn gebaseerd op longitudinale data van adolescenten tussen de 11 en 16 jaar oud die meededen aan het Digital Youth (DiYo) project tussen 2015 en 2019 (Van den Eijnden et al., 2018). Het doel van het DiYo project is om inzicht te verkrijgen in online gedragingen en welbevinden van adolescenten. Adolescenten die meededen aan het DiYo project vulden jaarlijks dezelfde vragenlijst in.

## Samenvatting van de Belangrijkste Resultaten

Uit onze resultaten volgen meerdere kernbevindingen (dikgedrukt). Ten eerste, **de SMD-schaal is geschikt om problematisch socialemediagebruik te meten bij adolescenten**; dit is niet alleen het geval in Nederland, maar ook in andere Europese landen en in Canada. Hoofdstuk 2 liet zien dat de schaal valide en betrouwbaar is voor gebruik onder Nederlandse adolescenten. Verder is de schaal geschikt om de prevalentie van problematisch socialemediagebruik te vergelijken tussen adolescenten die verschillen in geslacht, leeftijd, het geboorteland van hun ouders en in opleidingsniveau. Drie subgroepen werden geïdentificeerd: normatieve gebruikers (geen symptomen of één symptoom van problematisch socialemediagebruik), riskante gebruikers (twee tot vijf symptomen van problematisch socialemediagebruik) en problematische gebruikers (zes tot negen symptomen van problematisch socialemediagebruik). Uit Hoofdstuk 3 bleek dat de schaal ook betrouwbaar en valide is voor het meten van problematisch sociale media gebruik in andere Europese landen en in Canada en dat de schaal geschikt is om de prevalentie van problematisch socialemediagebruik te vergelijken tussen adolescenten uit verschillende landen.

Ten tweede, **niet zozeer de intensiteit van het socialemediagebruik, maar met name problematisch socialemediagebruik hangt samen met een verminderd welbevinden van adolescenten**. In ons internationale onderzoek rapporteerden problematische socialemediagebruikers een lagere mentale gezondheid en een verminderd sociaal welbevinden en welbevinden op school dan niet-problematische gebruikers. Daarentegen ging intensief socialemediagebruik niet, of alleen in specifieke gevallen, samen met een verminderd(e) mentale gezondheid, sociaal welbevinden en welbevinden op school (Hoofdstuk 4). Uit ons longitudinale onderzoek bleek dat een toename in problematisch socialemediagebruik binnen een adolescent samenhing met een afname in mentale gezondheid van diezelfde adolescent in het daaropvolgende jaar. Specifiek was er sprake van een toename in ADHD-symptomen en depressieve symptomen en een afname in levenstevredenheid. Bovendien was een toename in problematisch socialemediagebruik gerelateerd aan een toename in opwaartse sociale vergelijkingen op sociale netwerksites en slachtofferschap van cyberpesten in het daaropvolgende jaar. Een toename in de intensiteit van socialemediagebruik voorspelde daarentegen geen veranderingen in ADHD-symptomen, symptomen van depressie, levenstevredenheid, opwaartse sociale vergelijkingen, of slachtofferschap van cyberpesten in het daaropvolgende jaar (Hoofdstukken 5 en 6). Als we niet naar individuele ontwikkelingen binnen adolescenten maar naar verschillen tussen adolescenten keken (Hoofdstuk 8), dan zagen we dat intensievere gebruikers van sociale media een lagere levenstevredenheid rapporteerden dan minder intensieve gebruikers. Dit verschil leek echter veroorzaakt te worden door problematisch socialemediagebruik, omdat problematische gebruikers vaker intensiever gebruik rapporteerden (Hoofdstuk 8).

Ten derde, **de relatie tussen problematisch socialemediagebruik en welbevinden is onafhankelijk van de context van landen**. In nagenoeg alle onderzochte landen rapporteerden problematische socialemediagebruikers een lager welbevinden dan niet-problematische gebruikers (Hoofdstukken 3 en 4).

Ten vierde, **een laag welbevinden kan zowel een voorspeller als een uitkomst van problematisch socialemediagebruik zijn en dit is mede afhankelijk van de gekozen statistische analysetechniek**. *Binnen* adolescenten was een stijging in problematisch socialemediagebruik voorspellend voor een toename in ADHD-symptomen en een daling in levenstevredenheid in het daaropvolgende jaar. Andersom waren een toename in ADHD-symptomen en daling in levenstevredenheid *binnen* adolescenten niet voorspellend voor een toename in problematisch socialemediagebruik in het daaropvolgende jaar (Hoofdstukken 5 en 6). Deze bevindingen suggereren dat een lager welbevinden eerder het gevolg dan de oorzaak van problematisch socialemediagebruik is. Deze suggestie behoeft echter nuancering, omdat deze uitsluitend is gebaseerd op de individuele ontwikkeling van problematisch socialemediagebruik en welbevinden binnen adolescenten over tijd. Uit andere statistische analyses waarbij naar verschillen *tussen* adolescenten werd gekeken, bleek namelijk dat adolescenten die meer ADHD-symptomen en een lagere levenstevredenheid ervaarden in vergelijking met andere adolescenten wel degelijk meer problematisch socialemediagebruik over tijd rapporteerden. Tezamen suggereren deze bevindingen dat verschillen in welbevinden *tussen adolescenten,* in plaats van veranderingen in welbevinden *binnen adolescenten*, het risico op problematisch socialemediagebruik beïnvloeden, terwijl veranderingen in problematisch socialemediagebruik *binnen adolescenten* tot een daling in welbevinden lijken te leiden.

Ten vijfde, **problematisch socialemediagebruik is stabiel over tijd**. We identificeerden vier groepen adolescenten met verschillende trajecten van problematisch gebruik en de intensiteit van gebruik van sociale media. In alle vier de groepen was het gemiddelde niveau van problematisch socialemediagebruik over het algemeen stabiel, namelijk gematigd hoog en stabiel of (zeer) laag en stabiel (Hoofdstuk 7). De intensiteit van socialemediagebruik liep niet per se parallel aan het niveau van problematisch socialemediagebruik. Bijvoorbeeld, adolescenten in de grootste groep van de vier geïdentificeerde groepen rapporteerden een stabiel laag niveau van problematisch socialemediagebruik, terwijl hun intensiteit van socialemediagebruik hoog was.

Ten zesde, **de relatie tussen de intensiteit van socialemediagebruik en welbevinden kan zowel positief als negatief zijn, afhankelijk van individuele kenmerken van de adolescent, de landencontext en het domein van welbevinden**. Voor sommige adolescenten ging een toename in de intensiteit van socialemediagebruik samen met een daling in levenstevredenheid, terwijl voor anderen een toename in de intensiteit van socialemediagebruik samenging met een stijging of helemaal geen verandering in levenstevredenheid (Hoofdstuk 8). De relatie hing bovendien af van de landencontext. Bijvoorbeeld, in landen waar intensief socialemediagebruik gebruikelijk was onder de adolescentenpopulatie, rapporteerden intensieve gebruikers *meer* levenstevredenheid dan niet-intensieve gebruikers, terwijl in landen waar intensief socialemediagebruik ongebruikelijk was, intensieve gebruikers *minder* levenstevredenheid dan niet-intensieve gebruikers rapporteerden (Hoofdstuk 4). Daarnaast verschilde de associatie per welbevindendomein. Uit ons internationale onderzoek bleek bijvoorbeeld dat intensieve socialemediagebruikers in alle landen meer steun van vrienden ervaarden dan niet-intensieve gebruikers, terwijl intensieve socialemediagebruikers in sommige landen een lager schoolwelbevinden rapporteerden dan niet-intensieve socialemediagebruikers (Hoofdstuk 4).

# Implicaties van de Bevindingen

## Conceptuele Implicaties

De bevinding dat de SMD-schaal betrouwbaar en valide is (Hoofdstukken 2 en 3), is een belangrijke stap voorwaarts in het meten van problematisch socialemediagebruik. De SMD-schaal zou kunnen bijdragen aan een betere conceptualisatie van problematisch socialemediagebruik, omdat de schaal ten opzichte van andere veelgebruikte schalen meer criteria omvat (Andreassen et al., 2012, 2016). Deze extra criteria zijn: *problemen* in belangrijke levensdomeinen vanwege socialemediagebruik, het *vervangen* van belangrijke activiteiten door socialemediagebruik en *liegen* over het socialemediagebruik. Door het toevoegen van deze criteria bij het meten van problematisch socialemediagebruik is de definitie van problematisch socialemediagebruik meer in lijn met de wetenschappelijke definitie van een gedragsverslaving en de diagnostische criteria van (meer) erkende gedragsverslavingen, zoals gok- en gameverslaving (American Psychiatric Association, 2013; Billieux, King, et al., 2017; Kardefelt-Winther et al., 2017).

Daarnaast suggereren onze bevindingen dat problematisch socialemediagebruik leidt tot een daling in mentale gezondheid en dat hogere niveaus van problematisch socialemediagebruik stabiel zijn over tijd (Hoofdstukken 5-7). Daarmee ondersteunt dit onderzoek het idee dat problematisch socialemediagebruik, zoals gemeten met de SMD-schaal, als een vorm van verslaving gezien kan worden. Deze bevinding is belangrijk in het licht van de terugkerende vraag of het mogelijk is om verslaafd te zijn aan normatieve dagelijkse activiteiten (Billieux, King, et al., 2017; Kardefelt-Winther et al., 2017; Van Rooij et al., 2018), zoals socialemediagebruik. Er is echter meer onderzoek nodig naar het verloop van en de consequenties van problematisch socialemediagebruik onder andere leeftijdsgroepen om vast te stellen of er sprake is van verslavingsgedrag.

## Methodologische Implicaties

De bevinding dat de negen items van de SMD-schaal geschikt zijn voor onderzoek naar problematisch socialemediagebruik (Hoofdstukken 2 en 3) is een belangrijke stap voor toekomstig onderzoek hiernaar. Dit impliceert dat onderzoekers de somscore van de schaal kunnen gebruiken om het niveau van problematisch socialemediagebruik onder adolescenten vast te stellen. Een alternatieve strategie is om adolescenten in te delen in subgroepen, gebaseerd op hun somscore: normatieve socialemediagebruikers (geen symptomen of één symptoom), riskante socialemediagebruikers (twee tot vijf symptomen) en problematische socialemediagebruikers (zes tot negen symptomen).

Ook het resultaat dat met name problematisch socialemediagebruik, en meestal niet de intensiteit van socialemediagebruik, negatief samenhangt met welbevinden heeft gevolgen voor toekomstig onderzoek. Aangezien deze twee dimensies van sociale media gecorreleerd zijn aan elkaar (Hoofdstukken 3 en 4), maar verschillen in hun relatie met welbevinden (Hoofdstukken 4-6 en 8), is het belangrijk dat toekomstig onderzoek naar het verband tussen de intensiteit van socialemediagebruik en welbevinden controleert op problematisch socialemediagebruik in de analyses. Dit verkleint namelijk de kans dat er een verband wordt gevonden tussen de intensiteit van socialemediagebruik en verminderd welbevinden dat eigenlijk verklaard wordt door problematisch socialemediagebruik.

Bovendien tonen onze bevindingen aan dat het waardevol is om de relatie tussen socialemediagebruik en welbevinden op verschillende manieren te onderzoeken: alhoewel veranderingen binnen adolescenten in welbevinden niet voorspellend waren voor veranderingen in problematisch socialemediagebruik in het daaropvolgende jaar (Hoofdstukken 5 en 6), toonden andere analyses aan dat stabiele verschillen in welbevinden tussen adolescenten voorspellend zijn voor relatief hoge niveaus van problematisch socialemediagebruik (Hoofdstuk 7). Door zowel het effect van stabiele verschillen *tussen adolescenten* als veranderingen over tijd *binnen adolescenten* in welbevinden op problematisch socialemediagebruik te onderzoeken, kan een completer beeld gegeven worden van de relatie.

## Theoretische Implicaties

De bevinding dat vooral problematisch socialemediagebruik en niet zozeer een hogere intensiteit van het gebruik samengaat met een lager welbevinden (Hoofdstukken 4-6, 8) is belangrijk voor het begrijpen van de relatie tussen socialemediagebruik en welbevinden. Het suggereert namelijk dat ongunstige effecten niet worden veroorzaakt door simpelweg veel gebruik te maken van sociale media, hetgeen regelmatig verondersteld wordt volgens de *displacement hypothesis* (Twenge, 2019; Underwood & Ehrenreich, 2017). Intensieve socialemediagebruikers kunnen hun gebruik meestal onder controle houden en dit afwisselen met activiteiten die belangrijk zijn voor hun welbevinden, zoals afspreken met vrienden. Onze resultaten lieten zelfs zien dat een hogere intensiteit van socialemediagebruik gerelateerd was aan het ervaren van meer steun van vrienden (Hoofdstuk 4), meer 'face-to-face' contact met vrienden (Hoofdstuk 6) en meer vriendschapscompetenties (Hoofdstuk 7). In lijn met de *stimulation hypothesis* (Valkenburg & Peter, 2007, 2011), kan intensief socialemediagebruik dus mogelijk bijdragen aan de sociale ontwikkeling van adolescenten en is het meestal geen risicogedrag. Negatieve effecten lijken vooral gedreven door problematisch socialemediagebruik, zoals controleverlies over het gebruik en het continue denken aan sociale media.

Een lagere levenstevredenheid was niet alleen een uitkomst van problematische socialemediagebruik (Hoofdstuk 6), maar ook een voorspeller (Hoofdstuk 7). Volgens het *cognitive behavioral model* van internetverslaving veroorzaken mentale gezondheidsproblemen destructieve gedachten, zoals de gedachte dat het desbetreffende gedrag (hier: socialemediagebruik) zorgen of negatieve gevoelens wegnemen. Dergelijke gedachten zouden vervolgens kunnen leiden tot problematisch socialemediagebruik (Davis, 2001). Bovendien ontwikkelen adolescenten met mentale gezondheidsproblemen mogelijk een voorkeur voor online in plaats van offline sociale interactie, omdat psychosociale kwetsbaarheden online minder zichtbaar zouden zijn. Hierdoor kunnen zij gevoeliger zijn voor problematisch socialemediagebruik (Caplan, 2003). Daarnaast lieten onze resultaten zien dat ADHD-symptomen ook voorspellend zijn voor problematisch socialemediagebruik (Hoofdstuk 7). Mogelijk zijn adolescenten met ADHD-symptomen gevoelig voor problematisch socialemediagebruik op eenzelfde manier als dat zij gevoelig zijn voor verslavingen gerelateerd aan middelengebruik, bijvoorbeeld omdat zij vanwege hun impulsiviteit doorgaans minder goed korte termijn behoeften kunnen weerstaan (Rømer Thomsen et al., 2018).

Onze bevindingen ondersteunen ook het *differential susceptibility to media effects model* (Valkenburg & Peter, 2013), hetgeen inhoudt dat media effecten afhankelijk zijn van individuele en contextuele factoren. De relatie tussen de intensiteit van socialemediagebruik en welbevinden verschilde namelijk tussen adolescenten en tussen landen (Hoofdstukken 4 en 8). De gevonden landenverschillen ondersteunen bovendien de *normalization hypothesis*: zodra een verondersteld risicogedrag (hier: intensief socialemediagebruik) de norm is binnen een populatie, vormt het desbetreffende risicogedrag geen bedreiging meer in die populatie en kan het zelfs indicatief zijn voor normatief of gezond gedrag (Haskuka et al., 2018; Sznitman et al., 2015).

Een theoretische verwachting die niet werd ondersteund door onze bevindingen was de *active versus passive use hypothesis*. Volgens deze theorie draagt actief socialemediagebruik, zoals het communiceren met leeftijdsgenoten via sociale media, positief bij aan het welbevinden, terwijl passief socialemediagebruik, zoals het bekijken van berichten of foto's van anderen op sociale media, negatief bijdraagt aan welbevinden (Dienlin & Johannes, 2020; Verduyn et al., 2017). Recent onderzoek vond ook geen bewijs voor deze theorie (Beyens, Pouwels, Van Driel, et al., 2020; Jensen et al., 2019; Valkenburg, Beyens, et al., 2021; Valkenburg, Van Driel, et al., 2021). Een verklaring hiervoor zou kunnen liggen in de complexiteit van het indelen van sociale media activiteiten in passief versus actief gebruik, omdat veel activiteiten zowel passieve als actieve componenten bevatten. Bovendien gaat passief gebruik, zoals het lezen van een bericht, doorgaans vooraf aan actief gebruik, zoals het reageren op een bericht.

## Praktische Implicaties

Uit de bovenstaande theoretische implicaties volgen ook implicaties voor de praktijk, al hoewel meer onderzoek naar het schadelijke effect van problematisch socialemediagebruik op welbevinden gewenst is om de praktische implicaties te onderbouwen. De bevinding dat eerder problematisch socialemediagebruik gerelateerd is aan een lager welbevinden dan een hoge intensiteit van socialemediagebruik is relevant voor ouders en leraren die bezorgd zijn over het socialemediagebruik van hun kinderen of leerlingen. Onze bevindingen suggereren dat intensief socialemediagebruik normatief gedrag is voor adolescenten, dat bovendien kan bijdragen aan het sociaal welbevinden. Het problematiseren van socialemediagebruik staat daarmee het begrijpen van het dagelijks leven van de hedendaagse adolescent mogelijk in de weg, aangezien sociale media daar vaak een belangrijk onderdeel van zijn. Desondanks is het belangrijk om na te gaan in hoeverre het socialemediagebruik problematisch is, dat wil zeggen gekenmerkt wordt door verslavingssymptomen, omdat we meerdere aanwijzingen hebben gevonden dat problematisch socialemediagebruik leidt tot een verlaagd welbevinden.

Aangezien problematisch socialemediagebruik negatief samenhing met meerdere domeinen van welbevinden, dit gevonden werd in meerdere landen en problematisch socialemediagebruik over het algemeen niet van tijdelijke aard was (Hoofdstukken 4-8), is het voor scholen en/of (overheids) instituten het overwegen waard om programma's te ontwikkelen gericht op het voorkomen en aanpakken van problematisch socialemediagebruik bij adolescenten. Alhoewel hoge niveaus van problematisch socialemediagebruik weinig voorkwamen (Hoofdstukken 2 en 3), werden gematigd hoge niveaus (oftewel riskant gebruik) regelmatig gerapporteerd (Hoofdstukken 2 en 7). Zowel adolescenten met hoge niveaus als gematigd hoge niveaus van problematisch gebruik hebben een hogere kans op het ervaren van problemen op belangrijke levensdomeinen (Hoofdstuk 2) en daarom is het ontwikkelen van dergelijke programma's wellicht relevant.

Preventie programma's zouden zich kunnen richten op de bewustwording van het socialemediagebruik in het algemeen. Zo heeft het Trimbos-instituut recent een website gelanceerd gericht op verkrijgen van inzicht in en promoten van een 'digitale balans'. Volgens de initiatiefnemers is voor een digitale balans niet zozeer schermtijd cruciaal, maar de mate waarin het socialemediagebruik ten koste gaat van het functioneren op belangrijke levensdomeinen (Trimbos-institute, 2020). Inzicht in het eigen sociale mediagedrag kan een belangrijk startpunt zijn voor het veranderen van gedrag, zoals problematisch socialemediagebruik (Throuvala et al., 2020). Daarnaast zijn interventies gericht op het behoud of terugkrijgen van controle op socialemediagebruik (Schiltkamp, 2021), zonder dat dit gepaard gaat met minder sociale betrokkenheid bij leeftijdsgenoten, wellicht waardevol.

Voor sommige adolescenten zou problematisch socialemediagebruik een symptoom van onderliggende mentale gezondheidsproblemen kunnen zijn (Hoofdstuk 7). Zij vertonen mogelijk problematisch gebruik omdat socialemediagebruik hen helpt om te gaan met hun problemen (Kuss & Griffiths, 2011, 2017). Deze adolescenten hebben mogelijk met name baat bij individuele hulpverlening gericht op hun onderliggende kwetsbaarheden.

## Toekomstig Onderzoek

De resultaten van het onderzoek uit dit proefschrift geven aanleiding tot verschillende suggesties voor vervolgonderzoek. Alhoewel onze bevindingen ondersteunen dat problematisch socialemediagebruik lijkt op verslavingsgedrag (Hoofdstukken 4-8), is er allereerst meer onderzoek nodig om dit te bevestigen, zoals onderzoek naar de ontwikkeling en consequenties van problematisch socialemediagebruik in andere leeftijdsgroepen. Bovendien is validatieonderzoek belangrijk waarin professionals uit de verslavingszorg door middel van diagnostische interviews nagaan of adolescenten die hoog scoren op de SMD-schaal daadwerkelijk verslavingskenmerken vertonen die in lijn zijn met kenmerken van erkende (gedrags)verslavingen (Kardefelt-Winther et al., 2017). Als uit meer onderzoek blijkt dat problematisch socialemediagebruik een gedragsverslaving is, dan kan het eventueel opgenomen worden als zodanig in een diagnostisch handboek, hetgeen professionele hulp aan problematische socialemediagebruikers faciliteert.

Om de gevonden relatie tussen problematisch socialemediagebruik en welbevinden beter te begrijpen, is ten tweede diepgaander onderzoek naar deze relatie nodig. Zo is er bijvoorbeeld nog weinig bekend over welke adolescenten meer en minder gevoelig zijn voor negatieve uitkomsten van problematisch socialemediagebruik. Daarnaast geeft ons onderzoek inzicht in de relatie tussen problematisch socialemediagebruik en welbevinden op de lange termijn (Hoofdstukken 5 en 6), maar is er nog weinig bekend over deze relatie op kortere termijn. Verder is het denkbaar dat de gevonden relaties tussen problematisch socialemediagebruik en welbevinden verklaard worden door onderliggende factoren die niet zijn gemeten in ons onderzoek (Caplan, 2003; Davis, 2001). Bovendien hebben we in ons onderzoek meer aandacht besteed aan de uitkomsten van problematisch socialemediagebruik dan de mogelijke oorzaken hiervan.

## Conclusie

Dit proefschrift benadrukt de verschillen tussen twee dimensies van socialemediagebruik: de intensiteit van socialemediagebruik, oftewel de frequentie van gebruik, en problematisch socialemediagebruik, oftewel kenmerken van verslaving ten aanzien van het gebruik. Over het algemeen is problematisch socialemediagebruik gerelateerd aan lager welbevinden, terwijl intensief gebruik dat meestal niet is. Bovendien suggereren onze bevindingen dat een hogere intensiteit van socialemediagebruik gunstig is voor het sociaal welbevinden van adolescenten. Om de wetenschappelijke kennis over de aard, oorzaken en gevolgen van problematisch socialemediagebruik verder te vergroten, biedt het huidige onderzoek een aantal aanknopingspunten voor verder onderzoek. Ons validatieonderzoek laat zien dat de SMD-schaal hiervoor geschikt is.

# References

Al-Menayes, J. J. (2015a). Psychometric properties and validation of the Arabic Social Media Addiction Scale. *Journal of Addiction*, *2015*, 1–6. https://doi.org/10.1155/2015/291743

Al-Menayes, J. J. (2015b). Social media use, engagement and addiction as predictors of academic performance. *International Journal of Psychological Studies*, *7*(4), 86–94. https://doi.org/10.5539/ijps.v7n4p86

American Psychiatric Association. (2013). *Diagnostic and statistical manual of mental disorders* (5th ed.). https://doi.org/10.1176/appi.books.9780890425596

Anderson, M., & Jiang, J. (2018). *Teens, social media & technology 2018*. https://www.pewresearch.org/internet/2018/05/31/teens-social-media-technology-2018/

Anderson, M., & Smith, A. (2021). *Social media use in 2021*. https://www.pewresearch.org/internet/2021/04/07/social-media-use-in-2021/

Andreassen, C. S. (2015). Online social network site addiction: A comprehensive review. *Current Addiction Reports*, *2*(2), 175–184. https://doi.org/10.1007/s40429-015-0056-9

Andreassen, C. S., Billieux, J., Griffiths, M. D., Kuss, D. J., Demetrovics, Z., Mazzoni, E., & Pallesen, S. (2016). The relationship between addictive use of social media and video games and symptoms of psychiatric disorders: A large-scale cross-sectional study. *Psychology of Addictive Behaviors*, *30*(2), 252–262. https://doi.org/10.1037/adb0000160

Andreassen, C. S., Torsheim, T., Brunborg, G. S., & Pallesen, S. (2012). Development of a Facebook Addiction Scale. *Psychological Reports*, *110*, 501–517. https://doi.org/10.2466/02.09.18.PR0.110.2.501-517

Apaolaza, V., Hartmann, P., D'Souza, C., & Gilsanz, A. (2019). Mindfulness, compulsive mobile social media use, and derived stress: The mediating roles of self-esteem and social anxiety. *Cyberpsychology, Behavior, and Social Networking*, *22*(6), 388–396. https://doi.org/10.1089/cyber.2018.0681

Apaolaza, V., Hartmann, P., Medina, E., Barrutia, J. M., & Echebarria, C. (2013). The relationship between socializing on the Spanish online networking site Tuenti and teenagers' subjective wellbeing: The roles of self-esteem and loneliness. *Computers in Human Behavior*, *29*(4), 1282–1289. https://doi.org/10.1016/j.chb.2013.01.002

Arnarsson, A., & Bjarnason, T. (2018). The problem with low-prevalence of bullying. *International Journal of Environmental Research and Public Health*, *15*(7). https://doi.org/10.3390/ijerph15071535

Asparouhov, T., Hamaker, E. L., & Muthén, B. O. (2017). Dynamic structural equation models. *Structural Equation Modeling: A Multidisciplinary Journal*, *25*(3), 1–30. https://doi.org/10.1080/10705511.2017.1406803

Asparouhov, T., & Muthén, B. O. (2010a). *Bayesian analysis using Mplus: Technical implementation*. Mplus Technical Appendices. https://www.statmodel.com/techappen.shtml

Asparouhov, T., & Muthén, B. O. (2010b). *Multiple imputation with Mplus*. Mplus Technical Appendices. https://www.statmodel.com/techappen.shtml

Asparouhov, T., & Muthén, B. O. (2010c). *Plausible values for latent variables using Mplus*. Mplus Technical Appendices. https://www.statmodel.com/techappen.shtml

Asparouhov, T., & Muthén, B. O. (2014). Auxiliary variables in mixture modeling: Three-step approaches using Mplus. *Structural Equation Modeling*, *21*(3), 329–341. https://doi.org/10.1080/10705511.2014.915181

Asparouhov, T., & Muthén, B. O. (2015). Residual associations in Latent Class and Latent Transition Analysis. *Structural Equation Modeling*, *22*(2), 169–177. https://doi.org/10.1080/10705511.2014.935844

Atkins, D. C., & Gallop, R. J. (2007). Rethinking how family researchers model infrequent outcomes: A tutorial on count regression and zero-inflated models. *Journal of Family Psychology*, *21*(4), 726–735. https://doi.org/10.1037/0893-3200.21.4.726

Baams, L., Van de Bongardt, D., & Doornwaard, S. M. (2017). *Codebook Project Stars: Studies on trajectories of adolescent relationships and sexuality* (pp. 46–47). https://easy.dans.knaw.nl/ui/datasets/id/easy-dataset:75299/tab/2

Bagozzi, R. P., & Yi, Y. (1988). On the evaluation of structural equation models. *Journal of the Academy of Marketing Science*, *16*(1), 74–94. https://doi.org/10.1007/BF02723327

Baker, F. B. (2001). Item characteristic curve models. In C. Boston & L. Rudner (Eds.), *The basics of item response theory* (pp. 21–34). ERIC Clearinghouse on Assessment and Evaluation.

Ballon, N., Brunault, P., & Cortese, S. (2015). Sensation seeking and cocaine dependence in adults with eeported childhood ADHD. *Journal of Attention Disorders*, *19*(4), 335–342. https://doi.org/10.1177/1087054714543651

Bányai, F., Zsila, Á., Király, O., Maraz, A., Elekes, Z., Griffiths, M. D., Andreassen, C. S., & Demetrovics, Z. (2017). Problematic social media use: Results from a large-scale nationally representative adolescent sample. *PLoS ONE*, *12*(1), 10–14. https://doi.org/10.1371/journal.pone.0169839

Barry, C. T., Sidoti, C. L., Briggs, S. M., Reiter, S. R., & Lindsey, R. A. (2017). Adolescent social media use and mental health from adolescent and parent perspectives. *Journal of Adolescence*, *61*, 1–11. https://doi.org/10.1016/j.adolescence.2017.08.005

Baumgartner, S. E., Van der Schuur, W. A., Lemmens, J. S., & Te Poel, F. (2017). The relationship between media multitasking and attention problems in adolescents: Results of two longitudinal studies. *Human Communication Research*, *44*(1), 3–30. https://doi.org/10.1111/hcre.12111

Bayer, J., Ellison, N., Schoenebeck, S., Brady, E., & Falk, E. B. (2018). Facebook in context(s): Measuring emotional responses across time and space. *New Media and Society*, *20*(3), 1047–1067. https://doi.org/10.1177/1461444816681522

Beeres, D. T., Andersson, F., Vossen, H. G. M., & Galanti, M. R. (2020). Social media and mental health among early adolescents in Sweden: A longitudinal study with 2-year follow-up (KUPOL Study). *Journal of Adolescent Health*, 1–8. https://doi.org/10.1016/j.jadohealth.2020.07.042

Best, P., Manktelow, R., & Taylor, B. (2014). Online communication, social media and adolescent wellbeing: A systematic narrative review. *Children and Youth Services Review*, *41*, 27–36. https://doi.org/10.1016/j.childyouth.2014.03.001

Beyens, I., Pouwels, J. L., Valkenburg, P. M., & Van Driel, I. I. (2020). The effect of social media on well-being differs from adolescent to adolescent. *Scientific Reports*, 1–11. https://doi.org/10.1038/s41598-020-67727-7

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

Billieux, J., King, D. L., Higuchi, S., Achab, S., Bowden-Jones, H., Hao, W., Long, J., Lee, H. K., Potenza, M. N., Saunders, J. B., & Poznyak, V. (2017). Functional impairment matters in the screening and diagnosis of gaming disorder. *Journal of Behavioral Addictions*, *6*(3), 285–289. https://doi.org/10.1556/2006.6.2017.036

Billieux, J., Van Rooij, A. J., Heeren, A., Schimmenti, A., Maurage, P., Edman, J., Blaszczynski, A., Khazaal, Y., & Kardefelt-Winther, D. (2017). Behavioural Addiction Open Definition 2.0—using the Open Science Framework for collaborative and transparent theoretical development. *Addiction*, *112*(10), 1723–1724. https://doi.org/10.1111/add.13938

Blau, I. (2011). Application use, online relationship types, self-disclosure, and Internet abuse among children and youth: Implications for education and Internet safety programs. *Journal of Educational Computing Research*, *45*(1), 95–116. https://doi.org/10.2190/ec.45.1.e

Boer, M., Stevens, G. W. J. M., Finkenauer, C., De Looze, M. E., & Van den Eijnden, R. J. J. M. (2021). Social media use intensity, social media use problems, and mental health among adolescents: Investigating directionality and mediating processes. *Computers in Human Behavior*, *116*(106645). https://doi.org/10.1016/j.chb.2020.106645

Boer, M., Stevens, G. W. J. M., Finkenauer, C., Koning, I. M., & Van den Eijnden, R. J. J. M. (2021). Validation of the Social Media Disorder Scale in Dutch adolescents: Findings from a large-scale nationally representative sample. *Assessment*. https://doi.org/10.1177/10731911211027232

Boer, M., Stevens, G. W. J. M., Finkenauer, C., & Van den Eijnden, R. J. J. M. (2020). Attention deficit hyperactivity disorder-symptoms, social media use intensity, and social media use problems in adolescents: Investigating directionality. *Child Development*, *91*(4), e853–e865. https://doi.org/10.1111/cdev.13334

Boer, M., Stevens, G. W. J. M., Finkenauer, C., & Van den Eijnden, R. J. J. M. (2021). The course of problematic social media use in young adolescents: A latent class growth analysis. *Child Development*, *in press*. https://doi.org/10.1111/cdev.13712

Boer, M., & Van den Eijnden, R. J. J. M. (2018). Sociale media en gamen [Social media and gaming]. In G. W. J. M. Stevens, S. A. F. M. Van Dorsselaer, M. Boer, S. A. De Roos, E. L. Duinhof, T. F. M. Ter Bogt, R. J. J. M. Van den Eijnden, L. S. Kuyper, D. M. Visser, W. A. M. Vollebergh, & M. E. De Looze (Eds.), *HBSC 2017: Gezondheid en welzijn van jongeren in Nederland [Health behavior in school-aged children in the Netherlands]* (pp. 135–147). Utrecht University, Netherlands.

Boer, M., Van den Eijnden, R. J. J. M., Boniel-Nissim, M., Wong, S.-L., Inchley, J., Badura, P., Craig, W. M., Gobina, I., Kleszczewska, D., Klanšček, H. J., & Stevens, G. W. J. M. (2020). Adolescents' intense and problematic social media use and their wellbeing in 29 countries. *Journal of Adolescent Health*, *66*(6), S89–S99. https://doi.org/10.1016/j.jadohealth.2020.02.014

Boers, E., Afzali, M. H., Newton, N., & Conrod, P. (2019). Association of screen time and depression in adolescence. *JAMA Pediatrics*, *173*(8), 853–859. https://doi.org/10.1001/jamapediatrics.2019.1759

Bollen, K. (2002). Latent variables in psychology and the social sciences. *Annual Review of Psychology*, *53*(1), 605–634. https://doi.org/10.1146/annurev.psych.53.100901.135239

Bollen, K., & Lennox, R. (1991). Conventional wisdom on measurement: A structural equation perspective. *Psychological Bulletin*, *110*(2), 305–314. https://doi.org/10.1037/0033-2909.110.2.305

Bongers, I. L., Koot, H. M., Van der Ende, J., & Verhulst, F. C. (2004). Developmental trajectories of externalizing behaviors in childhood and adolescence. *Child Development*, *75*(5), 1523–1537. https://doi.org/10.1111/j.1467-8624.2004.00755.x

Boyd, D. (2014). *It's complicated: The social lives of networked teens*. Yale University Press.

Brand, M., Rumpf, H., Demetrovics, Z., Müller, A., Stark, R., King, D. L., Goudriaan, A. E., Mann, K., Trotzke, P., Fineberg, N. A., Chamberlain, S. R., Kraus, S. W., Wegmann, E., Billieux, J., & Potenza, M. N. (2020). Which conditions should be considered as disorders in the International Classification of Diseases (ICD-11) designation of "other specified disorders due to addictive behaviors"? *Journal of Behavioral Addictions*, 1–10. https://doi.org/10.1556/2006.2020.00035

Brand, M., Wegmann, E., Stark, R., Müller, A., Wölfling, K., Robbins, T. W., & Potenza, M. N. (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 and Biobehavioral Reviews*, *104*, 1–10. https://doi.org/10.1016/j.neubiorev.2019.06.032

Brännlund, A., Strandh, M., & Nilsson, K. (2017). Mental-health and educational achievement: The link between poor mental-health and upper secondary school completion and grades. *Journal of Mental Health*, *26*(4), 318–325. https://doi.org/10.1080/09638237.2017.1294739

Brechwald, W. A., & Prinstein, M. J. (2011). Beyond homophily: A decade of advances in understanding peer influence processes. *Journal of Research on Adolescence*, *21*(1), 166–179. https://doi.org/10.1111/j.1532-7795.2010.00721.x

Burke, M., & Kraut, R. E. (2016). The relationship between Facebook use and well-being depends on communication type and tie strength. *Journal of Computer-Mediated Communication*, *21*(4), 265–281. https://doi.org/10.1111/jcc4.12162

Burnham, K. P., & Anderson, D. R. (2004). Multimodel inference. *Sociological Methods & Research*, *33*(2), 261–304. https://doi.org/10.1177/0049124104268644

Butler, R. J., & Gasson, S. L. (2005). Self esteem/self concept scales for children and adolescents: A review. *Child and Adolescent Mental Health*, *10*(4), 190–201. https://doi.org/10.1111/j.1475-3588.2005.00368.x

Cabral, J. (2011). Is generation Y addicted to social media? *The Elon Journal of Undergraduate Research in Communications*, *2*(1), 5–21.

Cantril, H. (1965). *The pattern of human concerns*. Rutgers University Press.

Caplan, S. E. (2003). Preference for online social interaction: A theory of problematic Internet use and psychosocial well-being. *Communication Research*, *30*(6), 625–648. https://doi.org/10.1177/0093650203257842

Casas, F., & Rees, G. (2015). Measures of children's subjective well-being: Analysis of the potential for cross-national comparisons. *Child Indicators Research*, *8*(1), 49–69. https://doi.org/10.1007/s12187-014-9293-z

Celeux, G., & Soromenho, G. (1996). An entropy criterion for assessing the number of clusters in a mixture model. *Journal of Classification*, *13*(2), 195–212. https://doi.org/10.1007/BF01246098

Central Bureau for Statistics. (2017). *Onderwijssoort naar opleidingsniveau ouders [Educational level by educational level of parents]*. https://www.cbs.nl/nl-nl/maatwerk/2018/51/onderwijssoort-naar-opleidingsniveau-ouders-2013-2017

Central Bureau for Statistics. (2018a). *Jaarraport integratie [Annual integration monitor]*. https://www.cbs.nl/nl-nl/publicatie/2018/47/jaarrapport-integratie-2018

Central Bureau for Statistics. (2018b). *VO; leerlingen, onderwijssoort in detail, leerjaar [Students and educational level, school year]*. http://statline.cbs.nl/Statweb

Central Bureau for Statistics. (2019a). *VO; leerlingen, onderwijssoort in detail, leerjaar [Secondary education; students, educational level, school year]*. https://opendata.cbs.nl/statline

Central Bureau for Statistics. (2019b). *Wat is het verschil tussen een westerse en niet-westerse allochtoon? [What is the difference between a western and non-western immigrant background?]*. https://www.cbs.nl/nl-nl/faq/specifiek/wat-is-het-verschil-tussen-een-westerse-en-niet-westerse-allochtoon-

Central Bureau for Statistics. (2021). *Secondary school; students, educational level, grade, migrant background*. https://opendata.cbs.nl/#/CBS/nl/dataset/80043ned/table?dl=48F76

Chassin, L., Pitts, S. C., & Prost, J. (2002). Binge drinking trajectories from adolescence to emerging adulthood in a high-risk sample: Predictors and substance abuse outcomes. *Journal of Consulting and Clinical Psychology*, *70*(1), 67–78. https://doi.org/10.1037/0022-006X.70.1.67

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

Chen, I. H., Pakpour, A. H., Leung, H., Potenza, M. N., Su, J. A., Lin, C. Y., & Griffiths, M. D. (2020). Comparing generalized and specific problematic smartphone/internet use: Longitudinal relationships between smartphone applicationbased addiction and social media addiction and psychological distress. *Journal of Behavioral Addictions*, *9*(2), 410–419. https://doi.org/10.1556/2006.2020.00023

Cheng, C., Lau, Y. ching, Chan, L., & Luk, J. W. (2021). Prevalence of social media addiction across 32 nations: Meta-analysis with subgroup analysis of classification schemes and cultural values. *Addictive Behaviors*, *117*, 106845. https://doi.org/10.1016/j.addbeh.2021.106845

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

Ciarrochi, J., Parker, P., Sahdra, B., Marshall, S., Jackson, C., Gloster, A. T., & Heaven, P. (2016). The development of compulsive internet use and mental health: A four-year study of adolescence. *Developmental Psychology*, *52*(2), 272–283. https://doi.org/10.1037/dev0000070

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences*. Lawrence Earlbam Associates.

Compas, B. E., Ey, S., & Grant, K. E. (1993). Taxonomy, assessment, and diagnosis of depression during adolescence. *Psychological Bulletin*, *114*(2), 323–344. https://doi.org/10.1037/0033-2909.114.2.323

Connolly, J., Geller, S., Marton, P., & Kutcher, S. (1992). Peer responses to social interaction with depressed adolescents. *Journal of Clinical Child Psychology*, *21*(4), 365–370. https://doi.org/10.1207/s15374424jccp2104_6

Costello, A. B., & Osborne, J. W. (2005). Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis. *Practical Assessment, Research & Education*, *10*, 1–9. https://doi.org/10.1.1.110.9154

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

Currie, C., Molcho, M., Boyce, W., Holstein, B., Torsheim, T., & Richter, M. (2008). Researching health inequalities in adolescents: The development of the Health Behaviour in School-Aged Children (HBSC) Family Affluence Scale. *Social Science and Medicine*, *66*(6), 1429–1436. https://doi.org/10.1016/j.socscimed.2007.11.024

Cyders, M. A., & Smith, G. T. (2009). Emotion-based dispositions to rash action: Positive and negative urgency. *Psychological Bulletin*, *134*(6), 807–828. https://doi.org/10.1037/a0013341

Davidov, E. (2010). Testing for comparability of human values across countries and time with the third round of the European Social Survey. *International Journal of Comparative Sociology*, *51*(3), 171–191. https://doi.org/10.1177/0020715210363534

Davis, R. A. (2001). Cognitive-behavioral model of pathological Internet use. *Computers in Human Behavior*, *17*(2), 187–195. https://doi.org/10.1016/S0747-5632(00)00041-8

De Looze, M. E., Van Dorsselaer, S. A. F. M., Stevens, G. W. J. M., Boniel-Nissim, M., Vieno, A., & Van den Eijnden, R. J. J. M. (2019). The decline in adolescent substance use across Europe and North America in the early twenty-first century: A result of the digital revolution? *International Journal of Public Health*, *64*(2), 229–240. https://doi.org/10.1007/s00038-018-1182-7

De Vries, D. A., Möller, A. M., Wieringa, M. S., Eigenraam, A. W., & Hamelink, K. (2018). Social comparison as the thief of joy: Emotional consequences of viewing strangers' Instagram posts. *Media Psychology*, *21*(2), 222–245. https://doi.org/10.1080/15213269.2016.1267647

Dekker, M. C., Ferdinand, R. F., Van Lang, N. D. J., Bongers, I. L., van der Ende, J., & Verhulst, F. C. (2007). Developmental trajectories of depressive symptoms from early childhood to late adolescence: Gender differences and adult outcome. *Journal of Child Psychology and Psychiatry and Allied Disciplines*, *48*(7), 657–666. https://doi.org/10.1111/j.1469-7610.2007.01742.x

Deutsch, A. R., Hoffman, L., & Wilcox, B. L. (2014). Sexual self-concept: Testing a hypothetical model for men and women. *Journal of Sex Research*, *51*(8), 932–945. https://doi.org/10.1080/00224499.2013.805315

Dienlin, T., & Johannes, N. (2020). The impact of digital technology use on adolescent well-being. *Dialogues in Clinical Neuroscience*, *22*(2), 135–142. https://doi.org/10.31887/DCNS.2020.22.2/tdienlin

Distefano, C., Zhu, M., & Mîndrilă, D. (2009). Understanding and using factor scores: Considerations for the applied researcher - practical assessment, research & avaluation. *Practical Assessment, Research & Evaluation*, *14*(20), 1–11. https://doi.org/10.1.1.460.8553

Du, J., Kerkhof, P., & Van Koningsbruggen, G. M. (2021). The reciprocal relationships between social media self-control failure, mindfulness and wellbeing: A longitudinal study. *PLoS ONE*, *16*(8), e0255648. https://doi.org/10.1371/journal.pone.0255648

Elgar, F. J., Gariépy, G., Torsheim, T., & Currie, C. (2017). Early-life income inequality and adolescent health and well-being. *Social Science and Medicine*, *174*, 197–208. https://doi.org/10.1016/j.socscimed.2016.10.014

Enders, C. K., & Bandalos, D. L. (2001). The relative performance of full information maximum likelihood estimation for missing data in structural equation models. *Structural Equation Modeling*, *8*(3), 430–457. https://doi.org/10.1207/S15328007SEM0803_5

Engels, R. C. M. E., Finkenauer, C., Meeus, W., & Deković, M. (2001). Parental attachment and adolescents' emotional adjustment: The associations with social skills and relational competence. *Journal of Counseling Psychology*, *48*(4), 428–439. https://doi.org/10.1037/0022-0167.48.4.428

Erikson, E. H. (1968). *Identity: Youth and crisis*. WW Norton & Company.

Eurostat. (2015). Children and young people in the digital world. In M. Kotzeva (Ed.), *Being young in Europe today* (pp. 191–208). Publications Office of the European Union. https://doi.org/10.2785/59267

Fabrigar, L. R., Wegener, D. T., MacCallum, R. C., & Strahan, E. J. (1999). Evaluating the use of exploratory factor analysis in psychological research. *Psychological Methods*, *4*, 272–299. https://doi.org/10.1016/0743-9547(91)90011-L

Fallone, G., Acebo, C., Arnedt, J. T., Seiger, R., & Carskadon, M. A. (2001). Effects of acute sleep restriction on behavior, sustained attentoin, and response inhibition in children. *Perceptual and Motor Skills*, *93*(1), 213–229. https://doi.org/10.2466/pms.2001.93.1.213

Fardouly, J., & Vartanian, L. R. (2016). Social media and body image concerns: Current research and future directions. *Current Opinion in Psychology*, *9*, 1–5. https://doi.org/10.1016/j.copsyc.2015.09.005

Feinstein, B. A., Hershenberg, R., Bhatia, V., Latack, J. A., Meuwly, N., & Davila, J. (2013). Negative social comparison on Facebook and depressive symptoms: Rumination as a mechanism. *Psychology of Popular Media Culture*, *2*(3), 161–170. https://doi.org/10.1037/a0033111

Frison, E., & Eggermont, S. (2017). Browsing, posting, and liking on Instagram: The reciprocal relationships between different types of Instagram use and adolescents' depressed mood. *Cyberpsychology, Behavior, and Social Networking*, *20*(10), 603–609. https://doi.org/10.1089/cyber.2017.0156

Frost, R., & Rickwood, D. (2017). A systematic review of the mental health outcomes associated with Facebook use. *Computers in Human Behavior*, *76*, 576–600. https://doi.org/10.1016/j.chb.2017.08.001

Fung, S. (2019). Cross-cultural validation of the Social Media Disorder scale. *Psychology Research and Behavior Management*, *12*, 683–690. https://doi.org/10.2147/PRBM.S216788

Gadermann, A. M., Guhn, M., Zumbo, B. D., & Columbia, B. (2012). Estimating ordinal reliability for Likert-type and ordinal item response data: A conceptual, empirical, and practical guide. *Practical Assessment, Research & Evaluation*, *17*(3). https://doi.org/10.7275/n560-j767

Gariepy, G., McKinnon, B., Sentenac, M., & Elgar, F. J. (2016). Validity and reliability of a brief symptom checklist to measure psychological health in school-aged children. *Child Indicators Research*, *9*(2), 471–484. https://doi.org/10.1007/s12187-015-9326-2

George, M. J., Beron, K., Vollet, J. W., Burnell, K., Ehrenreich, S. E., & Underwood, M. K. (2020). Frequency of text messaging and adolescents' mental health symptoms across 4 years of high school. *Journal of Adolescent Health*. https://doi.org/10.1016/j.jadohealth.2020.06.012

Gollwitzer, P. M., & Sheeran, P. (2006). Implementation intentions and goal achievement: A meta-analysis of effects and processes. *Advances in Experimental Social Psychology*, *38*(06), 69–119. https://doi.org/10.1016/S0065-2601(06)38002-1

Gomez, R., Stavropoulos, V., Beard, C., & Pontes, H. M. (2019). Item response theory analysis of the recoded Internet Gaming Disorder Scale-short-form (IGDS9-SF). *International Journal of Mental Health and Addiction*, *17*(4), 859–879. https://doi.org/10.1007/s11469-018-9890-z

Goodman, R., Meltzer, H., & Bailey, V. (1998). The Strengths and Difficulties Questionnaire: A pilot study on the validity of the self-report version. *European Child & Adolescent Psychiatry*, *7*, 125–130. https://doi.org/10.1080/0954026021000046137

Granic, I., Morita, H., & Scholten, H. (2020). Beyond screen time: Identity development in the digital age. *Psychological Inquiry*, *31*(3), 195–223. https://doi.org/10.1080/1047840X.2020.1820214

Griffioen, N., Scholten, H., Lichtwarck-Aschoff, A., Van Rooij, M., & Granic, I. (2021). Everyone does it—differently: A window into emerging adults' smartphone use. *Humanities and Social Sciences Communications*, *8*(1), 1–11. https://doi.org/10.1057/s41599-021-00863-1

Griffiths, M. D. (2005). A "components" model of addiction within a biopsychosocial framework. *Journal of Substance Use*, *10*(4), 191–197. https://doi.org/10.1080/14659890500114359

Griffiths, M. D. (2010). The role of context in online gaming excess and addiction: Some case study evidence. *International Journal of Mental Health and Addiction*, *8*(1), 119–125. https://doi.org/10.1007/s11469-009-9229-x

Griffiths, M. D. (2013). Social networking addiction: Emerging themes and issues. *Journal of Addiction Research & Therapy*, *4*(5), 1–2. https://doi.org/10.4172/2155-6105.1000e118

Griffiths, M. D., & Kuss, D. J. (2011). Adolescent social networking: Should parents and teachers be worried? *Education and Health*, *29*(2), 23–25.

Griffiths, M. D., & Kuss, D. J. (2017). Adolescent social media addiction (revisited). *Education and Health*, *35*(3), 49–52.

Griffiths, M. D., Kuss, D. J., & Demetrovics, Z. (2014). Social networking addiction: An overview of preliminary findings. In K. P. Rosenberg & L. C. Feder (Eds.), *Behavioral addictions* (pp. 119–141). Academic Press. https://doi.org/10.1016/B978-0-12-407724-9.00006-9

Hallquist, M. N., & Wiley, J. F. (2018). MplusAutomation: An R package for facilitating large-scale latent variable analyses in Mplus. *Structural Equation Modeling*, *25*, 621–638. https://doi.org/10.1080/10705511.2017.1402334

Hamaker, E. L. (2012). Why researchers should think “within-person”: A paradigmatic rationale. In M. R. Mehl & T. S. Conner (Eds.), *Handbook of research methods for studying daily life* (pp. 43–61). Guilford.

Hamaker, E. L. (2018). *How to run the RI-CLPM with Mplus*. Special Mplus topics: RI-CLPM. http://www.statmodel.com/RI-CLPM.shtml

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

Harter, S. (2012). *Self-perception profile for adolescents: Manual and questionnaires*. University of Denver.

Haskuka, M., Arenliu, A., & Kelmendi, K. (2018). The relationship between substance use and suicidal behaviour among adolescents in selected European countries: A test of normalisation theory. *Drugs: Education, Prevention and Policy*, *25*(5), 413–421. https://doi.org/10.1080/09687637.2017.1308468

Haugland, S., & Wold, B. (2001). Subjective health complaints in adolescence - Reliability and validity of survey methods. *Journal of Adolescence*, *24*(5), 611–624. https://doi.org/10.1006/jado.2000.0393

Heffer, T., Good, M., Daly, O., MacDonell, E., & Willoughby, T. (2019). The longitudinal association between social-media use and depressive symptoms among adolescents and young adults: An empirical reply to Twenge et al. (2018). *Clinical Psychological Science*, *7*(3), 462–470. https://doi.org/10.1177/2167702618812727

Herrman, H., Saxena, S., & Moodie, R. (2005). Promoting mental health—concepts, emerging evidence, practice. In H. Herrman, S. Saxena, & R. Moodie (Eds.), *The Handbook of Community Mental Health Nursing*. World Health Organization. https://doi.org/10.5840/ncbq201616462

Hirshkowitz, M., Whiton, K., Albert, S. M., Alessi, C., Bruni, O., DonCarlos, L., Hazen, N., Herman, J., Adams Hillard, P. J., Katz, E. S., Kheirandish-Gozal, L., Neubauer, D. N., O’Donnell, A. E., Ohayon, M., Peever, J., Rawding, R., Sachdeva, R. C., Setters, B., Vitiello, M. V, & Ware, J. C. (2015). National Sleep Foundation’s updated sleep duration recommendations: Final report. *Sleep Health*, *1*(4), 233–243. https://doi.org/10.1016/j.sleh.2015.10.004

Hjetland, G. J., Schønning, V., Hella, R. T., Veseth, M., & Skogen, J. C. (2021). How do Norwegian adolescents experience the role of social media in relation to mental health and well-being: a qualitative study. *BMC Psychology*, *9*(1), 1–14. https://doi.org/10.1186/s40359-021-00582-x

Ho, S., Lwin, M., & Lee, E. (2017). Till logout do us part? Comparison of factors predicting excessive social network sites use and addiction between Singaporean adolescents and adults. *Computers in Human Behavior*, *75*, 632–642. https://doi.org/10.1016/j.chb.2017.06.002

Houghton, S., Lawrence, D., Hunter, S. C., Rosenberg, M., Zadow, C., Wood, L., & Shilton, T. (2018). Reciprocal relationships between trajectories of depressive symptoms and screen media use during adolescence. *Journal of Youth and Adolescence*, *47*(11), 2453–2467. https://doi.org/10.1007/s10964-018-0901-y

Howard, M. C. (2016). A review of exploratory factor analysis decisions and overview of current practices: What we are doing and how can we improve? *International Journal of Human-Computer Interaction*, *32*(1), 51–62. https://doi.org/10.1080/10447318.2015.1087664

Hox, J. (2010a). Analyzing longitudinal data. In J. Hox (Ed.), *Multilevel analysis: Techniques and applications* (2nd ed., pp. 79–111). Routlegde.

Hox, J. (2010b). Estimation and hypothesis testing in multilevel regression. In J. Hox (Ed.), *Multilevel analysis: Techniques and applications* (2nd ed., pp. 40–51). Routlegde.

Hox, J. (2010c). Some important methodological and statistical issues. In J. Hox (Ed.), *Multilevel analysis: Techniques and applications* (2nd ed., pp. 54–78). Routledge.

Hox, J. (2010d). The basic two-level regression model. In J. Hox (Ed.), *Multilevel analysis: Techniques and applications* (2nd ed., pp. 11–39). Routledge.

Hox, J., Maas, C. J. M., & Brinkhuis, M. J. S. (2010). The effect of estimation method and sample size in multilevel structural equation modeling. *Statistica Neerlandica*, *64*(2), 157–170. https://doi.org/10.1111/j.1467-9574.2009.00445.x

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling*, *6*(1), 1–55. https://doi.org/10.1080/10705519909540118

Huang, C. (2017). Time spent on social network sites and psychological well-being: A meta-analysis. *Cyberpsychology, Behavior, and Social Networking*, *20*(6), 346–354. https://doi.org/10.1089/cyber.2016.0758

Huang, C. (2020). A meta-analysis of the problematic social media use and mental health. *International Journal of Social Psychiatry*, 1–20. https://doi.org/10.1177/0020764020978434

Huebner, E. S. (1991). Initial development of the student's life satisfaction scale. *School Psychology International, 12*(3), 231–240. https://doi.org/10.1177/0143034391123010

Huebner, E. S. (2004). Research on assessment of life satisfaction of chidren and adolescents. *Social Indicators Research*, *66*(1–2), 3–33. https://doi.org/10.1023/b:soci.0000007497.57754.e3

Inchley, J., Currie, D., Budisavljevic, S., Torsheim, T., Jåstad, A., Cosma, A., Kelly, C., Arnarsson, Á. M., & Samdal, O. (2020a). *Spotlight on adolescent health and well-being. Findings from the 2017/2018 Health Behaviour in School-aged Children (HBSC) survey in Europe and Canada. International report: Online methods annex (Volume 3).* http://www.hbsc.org/publications/international/

Inchley, J., Currie, D., Budisavljevic, S., Torsheim, T., Jåstad, A., Cosma, A., Kelly, C., Arnarsson, Á., & Samdal, O. (2020b). *Spotlight on adolescent health and well-being. Findings from the 2017/2018 Health Behaviour in School-aged Children (HBSC) survey in Europe and Canada. International report: Key data (Volume 2)*. http://www.hbsc.org/publications/international/

Inchley, J., Currie, D., Cosma, A., & Samdal, O. (2018). *Health Behaviour in School-aged Children (HBSC) study protocol: background, methodology and mandatory items for the 2017/18 survey*. http://www.hbsc.org/methods/

Inchley, J., Currie, D., Young, T., Samdal, O., Torsheim, T., Augustson, L., ..., & Barnekow, V. (2016). *Growing up unequal: Gender and socioeconomic differences in young people's health and well-being. Health Behaviour in School-aged Children (HBSC) study: International report from the 2013/2014 survey*. http://www.hbsc.org/publications/international/

Jameel, S., Shahnawaz, M. G., & Griffiths, M. D. (2019). Smartphone addiction in students: A qualitative examination of the components model of addiction using face-to-face interviews. *Journal of Behavioral Addictions*, *8*(4), 780–793. https://doi.org/10.1556/2006.8.2019.57

Jensen, M., George, M. J., Russell, M. R., & Odgers, C. L. (2019). Young adolescents' digital technology use and mental health symptoms: Little evidence of longitudinal or daily linkages. *Clinical Psychological Science*, *7*(6), 1416–1433. https://doi.org/10.1177/2167702619859336

Junco, R. (2013). Comparing actual and self-reported measures of Facebook use. *Computers in Human Behavior*, *29*(3), 626–631. https://doi.org/10.1016/j.chb.2012.11.007

Jung, T., & Wickrama, K. A. S. (2008). An introduction to latent class growth analysis and growth mixture modeling. *Social and Personality Psychology Compass*, *2*(1), 302–317. https://doi.org/10.1111/j.1751-9004.2007.00054.x

Kandel, D. B., & Davies, M. (1982). Epidemiology of depressive mood in adolescents: An empirical study. *Archives of General Psychiatry*, *39*(10), 1205–1212.

Kardefelt-Winther, D., Heeren, A., Schimmenti, A., Van Rooij, A. J., Maurage, P., Carras, M., Edman, J., Blaszczynski, A., Khazaal, Y., & Billieux, J. (2017). How can we conceptualize behavioural addiction without pathologizing common behaviours? *Addiction*, *112*(10), 1709–1715. https://doi.org/10.1111/add.13763

Karpinski, A. C., Kirschner, P. A., Ozer, I., Mellott, J. A., & Ochwo, P. (2013). An exploration of social networking site use, multitasking, and academic performance among United States and European university students. *Computers in Human Behavior*, *29*(3), 1182–1192. https://doi.org/10.1016/j.chb.2012.10.011

Keijsers, L., & Roekel, R. van. (2018). Longitudinal methods in adolescent psychology. Where could we go from here? And should we? In L. B. Hendry & M. Kloep (Eds.), *Reframing adolescent research*. Routledge.

Kelly, Y., Zilanawala, A., Booker, C., & Sacker, A. (2018). Social media use and adolescent mental health: Findings from the UK Millennium Cohort Study. *EClinicalMedicine*, *6*, 59–68. https://doi.org/10.1016/j.eclinm.2018.12.005

Kennisnet. (2017). *Monitor jeugd en media 2017 [youth and media 2017]*. https://www.kennisnet.nl/artikel/6713/

Király, O., Sleczka, P., Pontes, H. M., Urbán, R., Griffiths, M. D., & Demetrovics, Z. (2017). Validation of the Ten-Item Internet Gaming Disorder Test (IGDT-10) and evaluation of the nine DSM-5 Internet Gaming Disorder criteria. *Addictive Behaviors*, *64*, 253–260. https://doi.org/10.1016/j.addbeh.2015.11.005

Király, O., Tóth, D., Urbán, R., Demetrovics, Z., & Maraz, A. (2017). Intense video gaming is not essentially problematic. *Psychology of Addictive Behaviors*, *31*(7), 807–817. https://doi.org/10.1037/adb0000316.supp

Kline, R. B. (2011). Estimation. In R. B. Kline (Ed.), *Principles and practice of structural equation modeling* (3rd ed., pp. 154–183). The Guilford Press.

Klinger, D. A., Freeman, J. G., Bilz, L., Liiv, K., Ramelow, D., Sebok, S. S., Samdal, O., Dür, W., & Rasmussen, M. (2015). Cross-national trends in perceived school pressure by gender and age from 1994 to 2010. *European Journal of Public Health*, *25*, 51–56. https://doi.org/10.1093/eurpub/ckv027

Kloosterman, R., & Van Beuningen, J. (2015). *Jongeren over sociale media [Adolescents about social media]*. https://www.cbs.nl/nl-nl/achtergrond/2015/47/jongeren-over-sociale-media

Kuss, D. J., & Billieux, J. (2017). Technological addictions: Conceptualisation, measurement, etiology and treatment. *Addictive Behaviors*, *64*, 231–233. https://doi.org/10.1016/j.addbeh.2016.04.005

Kuss, D. J., & Griffiths, M. D. (2011). Online social networking and addiction: A review of the psychological literature. *International Journal of Environmental Research and Public Health*, *8*(9), 3528–3552. https://doi.org/10.3390/ijerph8093528

Kuss, D. J., & Griffiths, M. D. (2017). Social networking sites and addiction: Ten lessons learned. *International Journal of Environmental Research and Public Health*, *14*(311), 1–17. https://doi.org/10.3390/ijerph14030311

Kuss, D. J., Griffiths, M. D., Karila, L., & Billieux, J. (2014). Internet addiction: A systematic review of epidemiological research for the last decade. *Current Pharmaceutical Design*, *20*(25), 4026–4052. https://doi.org/10.2174/13816128113199990617

La Barbera, D., La Paglia, F., & Valsavoia, R. (2009). Social network and addiction. *Annual Review of CyberTherapy and Telemedicine*, *7*(1), 33–36. https://doi.org/10.3233/978-1-60750-017-9-33

LaFontana, K. M., & Cillessen, A. H. N. (2010). Developmental changes in the priority of perceived status in childhood and adolescence. *Social Development*, *19*(1), 130–147. https://doi.org/10.1111/j.1467-9507.2008.00522.x

Lambert, N. M., & Hartsough, C. S. (1998). Prospective study of tobacco smoking and substance dependencies among samples of ADHD and non-ADHD participants. *Journal of Learning Disabilities*, *31*(6), 533–544. https://doi.org/10.1177/002221949803100603

Ledesma, R. D., & Valero-Mora, P. (2007). Determining the number of factors to retain in EFA: An easy-to-use computer program for carrying out Parallel Analysis. *Practical Assessment, Research and Evaluation*, *12*(2). https://doi.org/10.7275/wjnc-nm63

Lee, E. W. J., Ho, S. S., & Lwin, M. O. (2017). Explicating problematic social network sites use: A review of concepts, theoretical frameworks, and future directions for communication theorizing. *New Media and Society*, *19*(2), 308–326. https://doi.org/10.1177/1461444816671891

Lemmens, J. S., Valkenburg, P. M., & Gentile, D. A. (2015). The Internet Gaming Disorder Scale. *Psychological Assessment*, *27*(2), 567–582. https://doi.org/10.1037/pas0000062

Lenhart, A., Duggan, M., Perrin, A., Stepler, R., Rainie, H., & Parker, K. (2015). *Teens, social media and technology overview 2015: Smartphones facilitate shifts in communication landscape for teens*. https://www.pewresearch.org/internet/2015/04/09/teens-social-media-technology-2015/

Levin, K. A., & Currie, C. (2014). Reliability and validity of an adapted version of the Cantril Ladder for use with adolescent samples. *Social Indicators Research*, *119*(2), 1047–1063. https://doi.org/10.1007/s11205-013-0507-4

Levine, L. E., Waite, B. M., & Bowman, L. L. (2007). Electronic media use, reading, and academic distractibility in college youth. *CyberPsychology & Behavior*, *10*(4), 560–566. https://doi.org/10.1089/cpb.2007.9990

Levine, L. E., Waite, B. M., & Bowman, L. L. (2012). Mobile media use, multitasking and distractibility. *International Journal of Cyber Behavior, Psychology and Learning*, *2*(3), 15–29. https://doi.org/10.4018/ijcbpl.2012070102

Li, J., Mo, P. K. H., Lau, J. T. F., Su, X., Zhang, X., Wu, A. M. S., Mai, J., & Chen, Y. (2018). Online social networking addiction and depression: The results from a large-scale prospective cohort study in Chinese adolescents. *Journal of Behavioral Addictions*, *7*(3), 686–696. https://doi.org/10.1556/2006.7.2018.69

Lin, C.-Y., Broström, A., Nilsen, P., Griffiths, M. D., & Pakpour, A. H. (2017). Psychometric validation of the Persian Bergen Social Media Addiction Scale using classic test theory and Rasch models. *Journal of Behavioral Addictions*, *6*(4), 620–629. https://doi.org/10.1556/2006.6.2017.071

Liu, D., Baumeister, R. F., Yang, C. C., & Hu, B. (2019). Digital communication media use and psychological well-being: A meta-analysis. *Journal of Computer-Mediated Communication*, *24*(5), 259–274. https://doi.org/10.1093/ccc/zmz013

Lüdtke, O., & Robitzsch, A. (2021). A critique of the Random Intercept Cross-Lagged Panel Model. *Preprint*. https://doi.org/10.31234/osf.io/6f85c

Madley-Dowd, P., Hughes, R., Tilling, K., & Heron, J. (2019). The proportion of missing data should not be used to guide decisions on multiple imputation. *Journal of Clinical Epidemiology*, *110*, 63–73. https://doi.org/10.1016/j.jclinepi.2019.02.016

Marengo, D., Longobardi, C., Fabris, M. A., & Settanni, M. (2018). Highly-visual social media and internalizing symptoms in adolescence: The mediating role of body image concerns. *Computers in Human Behavior*, *82*, 63–69. https://doi.org/10.1016/j.chb.2018.01.003

Marengo, D., Poletti, I., & Settanni, M. (2020). The interplay between neuroticism, extraversion, and social media addiction in young adult Facebook users: Testing the mediating role of online activity using objective data. *Addictive Behaviors*, *102*, 106150. https://doi.org/10.1016/j.addbeh.2019.106150

Marino, C., Finos, L., Vieno, A., Lenzi, M., & Spada, M. M. (2017). Objective Facebook behaviour: Differences between problematic and non-problematic users. *Computers in Human Behavior*, *73*, 541–546. https://doi.org/10.1016/j.chb.2017.04.015

Marino, C., Gini, G., Vieno, A., & Spada, M. M. (2018a). A comprehensive meta-analysis on Problematic Facebook Use. *Computers in Human Behavior*, *83*, 262–277. https://doi.org/10.1016/j.chb.2018.02.009

Marino, C., Gini, G., Vieno, A., & Spada, M. M. (2018b). The associations between problematic Facebook use, psychological distress and well-being among adolescents and young adults: A systematic review and meta-analysis. *Journal of Affective Disorders*, *226*, 274–281. https://doi.org/10.1016/j.jad.2017.10.007

Martin, C. S., Chung, T., Kirisci, L., & Langenbucher, J. W. (2006). Item response theory analysis of diagnostic criteria for alcohol and cannabis use disorders in adolescents: Implications for DSM-V. *Journal of Abnormal Psychology*, *115*(4), 807–814. https://doi.org/10.1037/0021-843X.115.4.807

Mascheroni, G., & Ólafsson, K. (2014). Different media for different contacts. In G. Mascheroni & K. Ólafsson (Eds.), *Net Children Go Mobile: Risks and opportunities* (2nd ed.). Educatt. https://doi.org/10.13140/RG.2.1.3590.8561

Mazur, J., Szkultecka-Dębek, M., Dzielska, A., Drozd, M., & Małkowska-Szkutnik, A. (2018). What does the Cantril Ladder measure in adolescence? *Archives of Medical Science*, *14*(1), 182–189. https://doi.org/10.5114/aoms.2016.60718

McCrory, A., Best, P., & Maddock, A. (2020). The relationship between highly visual social media and young people's mental health: A scoping review. *Children and Youth Services Review*, *115*, 105053. https://doi.org/10.1016/j.childyouth.2020.105053

Meeus, W., Van de Schoot, R., Keijsers, L., Schwartz, S. J., & Branje, S. (2010). On the progression and stability of adolescent identity formation: A five-wave longitudinal study in early-to-middle and middle-to-late adolescence. *Child Development*, *81*(5), 1565–1581. https://doi.org/10.1111/j.1467-8624.2010.01492.x

Meier, A., & Reinecke, L. (2020). Computer-mediated communication, social media, and mental health: A conceptual and empirical meta-review. *Communication Research*, 1–28. https://doi.org/10.1177/0093650220958224

Meijman, T. F., De Vries-Griever, A. H., De Vries, G., & Kampman, R. (2006). The evaluation of the Groningen Sleep Quality Scale. *Heymans Bulletin (HB 88-13-EX)*.

Mérelle, S., Kleiboer, A., Schotanus, M., Cluitmans, T., & Waardenburg, C. (2017). Which health-related problems are associated with problematic video-gaming or social media use in adolescents? A large-scale cross-sectional study. *Clinical Neuropsychiatry*, *14*(1), 11–19.

Michie, S., Van Stralen, M. M., & West, R. (2011). The behaviour change wheel: A new method for characterising and designing behaviour change interventions. *Implementation Science*, *6*(1), 1–12. https://doi.org/10.1186/1748-5908-6-42

Monacis, L., De Palo, V., Griffiths, M. D., & Sinatra, M. (2017). Social networking addiction, attachment style, and validation of the Italian version of the Bergen Social Media Addiction Scale. *Journal of Behavioral Addictions*, *6*(2), 178–186. https://doi.org/10.1556/2006.6.2017.023

Mulder, J. D., & Hamaker, E. L. (2021). Three extensions of the Random Intercept Cross-Lagged Panel Model. *Structural Equation Modeling: A Multidisciplinary Journal*, *28*(4), 638–648. https://doi.org/10.1080/10705511.2020.1784738

Müller, K., Dreier, M., Beutel, M., Duven, E., Giralt, S., & Wölfling, K. (2016). A hidden type of internet addiction? Intense and addictive use of social networking sites in adolescents. *Computers in Human Behavior*, *55*, 172–177. https://doi.org/10.1016/j.chb.2015.09.007

Muthén, B. O. (2004). Appendix 11: Estimation of factor scores. In B. O. Muthén (Ed.), *Mplus Technical Appendices* (pp. 47–48). Muthén & Muthén.

Muthén, L. K., & Muthén, B. O. (2002). How to use a Monte Carlo study to decide on sample size and determine power. *Structural Equation Modeling*, *9*(4), 599–620. https://doi.org/10.1207/S15328007SEM0904_8

Muthén, L. K., & Muthén, B. O. (2017a). Chapter 18: OUTPUT, SAVEDATA, and PLOT commands. In L. K. Muthén & B. O. Muthén (Eds.), *Mplus User's Guide. Eighth Edition.* (pp. 791–858). Muthén & Muthén.

Muthén, L. K., & Muthén, B. O. (2017b). *Mplus user's guide* (8th ed.). Muthén & Muthén.

Muthén, L. K., & Muthén, B. O. (2017c). Special modeling issues. In L. K. Muthén & B. O. Muthén (Eds.), *Mplus User's Guide. Eighth Edition.* (pp. 515–562). Muthén & Muthén.

Nesi, J., Miller, A. B., & Prinstein, M. J. (2017). Adolescents' depressive symptoms and subsequent technology-based interpersonal behaviors: A multi-wave study. *Journal of Applied Developmental Psychology*, *51*, 12–19. https://doi.org/10.1016/j.appdev.2017.02.002

Nesi, J., & Prinstein, M. J. (2015). Using social media for social comparison and feedback-seeking: Gender and popularity moderate associations with depressive symptoms. *Journal of Abnormal Child Psychology*, *43*(8), 1427–1438. https://doi.org/10.1007/s10802-015-0020-0

Nikkelen, S. W. C., Valkenburg, P. M., Huizinga, M., & Bushman, B. J. (2014). Media use and ADHD-related behaviors in children and adolescents: A meta-analysis. *Developmental Psychology*, *50*(9), 2228–2241. https://doi.org/10.1037/a0037318

Nylund, K. L., Asparouhov, T., & Muthén, B. O. (2007). Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. *Structural Equation Modeling*, *14*(4), 535–569. https://doi.org/10.1080/10705510701575396

O'Keeffe, G. S., Clarke-Pearson, K., Mulligan, D. A., Altmann, T. R., Brown, A., Christakis, D. A., Falik, H. L., Hill, D. L., Hogan, M. J., Levine, A. E., & Nelson, K. G. (2011). Clinical report - The impact of social media on children, adolescents, and families. *Pediatrics*, *127*(4), 800–804. https://doi.org/10.1542/peds.2011-0054

O'Leary, D., & Volkmer, S. A. (2021). Are the negative effects of social networking a privilege of the rich? Social network usage and life satisfaction across European countries. *Computers in Human Behavior Reports*, *3*(March), 100078. https://doi.org/10.1016/j.chbr.2021.100078

O'Reilly, M. (2020). Social media and adolescent mental health: The good, the bad and the ugly. *Journal of Mental Health*, *29*(2), 200–206. https://doi.org/10.1080/09638237.2020.1714007

Odgers, C. L., & Jensen, M. R. (2020). Annual research review: Adolescent mental health in the digital age: facts, fears, and future directions. *Journal of Child Psychology and Psychiatry and Allied Disciplines*, *61*(3), 336–348. https://doi.org/10.1111/jcpp.13190

Odgers, C. L., Schueller, S. M., & Ito, M. (2020). Screen time, social media use, and adolescent development. *Annual Review of Developmental Psychology*, *2*(1), 485–502. https://doi.org/10.1146/annurev-devpsych-121318-084815

OECD. (2019). *OECD Broadband Portal*. https://www.oecd.org/sti/broadband/broadband-statistics/

Ohlmeier, M. D., Peters, K., Te Wildt, B. T., Zedler, M., Ziegenbein, M., Wiese, B., Emrich, H. M., & Schneider, U. (2008). Comorbidity of alcohol and substance dependence with attention-deficit/hyperactivity disorder (ADHD). *Alcohol and Alcoholism*, *43*(3), 300–304. https://doi.org/10.1093/alcalc/agn014

Orben, A. (2020a). Teenagers, screens and social media: A narrative review of reviews and key studies. *Social Psychiatry and Psychiatric Epidemiology*, *55*(4), 407–414. https://doi.org/10.1007/s00127-019-01825-4

Orben, A. (2020b). The Sisyphean cycle of technology panics. *Perspectives on Psychological Science*, *15*(5), 1143–1157. https://doi.org/10.1177/1745691620919372

Orben, A., Dienlin, T., & Przybylski, A. K. (2019). Social media's enduring effect on adolescent life satisfaction. *Proceedings of the National Academy of Sciences*, 201902058. https://doi.org/10.1073/pnas.1902058116

Orben, A., & Przybylski, A. K. (2019a). Screens, teens, and psychological well-being: Evidence from three time-use-diary studies. *Psychological Science*, *30*(5), 682–696. https://doi.org/10.1177/0956797619830329

Orben, A., & Przybylski, A. K. (2019b). The association between adolescent well-being and digital technology use. *Nature Human Behaviour*. https://doi.org/10.1038/s41562-018-0506-1

Orth, U., Clark, D. A., Donnellan, M. B., & Robins, R. W. (2021). Testing prospective effects in longitudinal research: Comparing seven competing cross-Lagged models. *Journal of Personality and Social Psychology*, *120*(4), 1013–1034. https://doi.org/10.1037/pspp0000358.supp

Paakkari, L., Tynjälä, J., Lahti, H., Ojala, K., & Lyyra, N. (2021). Problematic social media use and health among adolescents. *International Journal of Environmental Research and Public Health*, *18*(4), 1–11. https://doi.org/10.3390/ijerph18041885

Parry, D. A., Davidson, B. I., Sewall, C. J. R., Fisher, J. T., & Quintana, S. (2020). Measurement discrepancies between logged and self-reported digital media use: A systematic review and meta-analysis. *Preprint*. https://doi.org/10.31234/osf.io/f6xvz

Peeters, M., Koning, I. M., Lemmens, J. S., & Van den Eijnden, R. J. J. M. (2019). Normative, passionate, or problematic? Identification of adolescent gamer subtypes over time. *Journal of Behavioral Addictions*, *8*(3), 574–585. https://doi.org/10.1556/2006.8.2019.55

Peeters, M., Zondervan-Zwijnenburg, M., Vink, G., & Van de Schoot, R. (2015). How to handle missing data: A comparison of different approaches. *European Journal of Developmental Psychology*, *12*(4), 377–394. https://doi.org/10.1080/17405629.2015.1049526

Pennay, A. E., & Measham, F. C. (2016). The normalisation thesis – 20 years later. *Drugs: Education, Prevention and Policy*, *23*(3), 187–189. https://doi.org/10.3109/09687637.2016.1173649

Pera, A. (2018). Psychopathological processes involved in social comparison, depression, and envy on Facebook. *Frontiers in Psychology*, *9*(January), 1–5. https://doi.org/10.3389/fpsyg.2018.00022

Phanasathit, M., Manwong, M., Hanprathet, N., Khumsri, J., & Yingyeun, R. (2015). Validation of the Thai version of Bergen Facebook Addiction Scale (Thai-BFAS). *Journal of the Medical Association of Thailand*, *98*, S108–S117.

Pielot, M., Church, K., & de Oliveira, R. (2014). An in-situ study of mobile phone notifications. *Proceedings of the 16th International Conference on Human-Computer Interaction with Mobile Devices & Services*, 233–242. https://doi.org/10.1145/2628363.2628364

Piteo, E. M., & Ward, K. (2020). Review: Social networking sites and associations with depressive and anxiety symptoms in children and adolescents – a systematic review. *Child and Adolescent Mental Health*, *25*(4), 201–216. https://doi.org/10.1111/camh.12373

Pontes, H. M. (2017). Investigating the differential effects of social networking site addiction and Internet gaming disorder on psychological health. *Journal of Behavioral Addictions*, *6*(4), 601–610. https://doi.org/10.1556/2006.6.2017.075

Pontes, H. M., Andreassen, C. S., & Griffiths, M. D. (2016). Portuguese validation of the Bergen Facebook Addiction Scale: An empirical study. *International Journal of Mental Health and Addiction*, *14*(6), 1062–1073. https://doi.org/10.1007/s11469-016-9694-y

Potenza, M. N. (2014). Non-substance addictive behaviors in the context of DSM-5. *Addictive Behaviors*, *39*(1). https://doi.org/10.1016/j.addbeh.2013.09.004

Pouwels, J. L., Valkenburg, P. M., Beyens, I., Van Driel, I. I., & Keijsers, L. (2021). Social media use and friendship closeness in adolescents' daily lives: An experience sampling study. *Developmental Psychology*, *57*(2), 309–323.

Primack, B. A., & Escobar-Viera, C. G. (2017). Social media as it interfaces with psychosocial development and mental illness in transitional age youth. *Child and Adolescent Psychiatric Clinics of North America*, *26*(2), 217–233. https://doi.org/10.1016/j.chc.2016.12.007

Primack, B. A., Shensa, A., Sidani, J. E., Whaite, E. O., Lin, L. yi, Rosen, D., Colditz, J. B., Radovic, A., & Miller, E. (2017). Social media use and perceived social isolation among young adults in the U.S. *American Journal of Preventive Medicine*, *53*(1), 1–8. https://doi.org/10.1016/j.amepre.2017.01.010

Proctor, C. L., Linley, P. A., & Maltby, J. (2009). Youth life satisfaction: A review of the literature. *Journal of Happiness Studies*, *10*(5), 583–630. https://doi.org/10.1007/s10902-008-9110-9

Przybylski, A. K., & Weinstein, N. (2017). A large-scale test of the Goldilocks Hypothesis: Quantifying the relations between digital-screen use and the mental well-being of adolescents. *Psychological Science*, *28*(2), 204–215. https://doi.org/10.1177/0956797616678438

Radovic, A., Gmelin, T., Stein, B. D., & Miller, E. (2017). Depressed adolescents' positive and negative use of social media. *Journal of Adolescence*, *55*, 5–15. https://doi.org/10.1016/j.adolescence.2016.12.002

Raudsepp, L. (2019). Brief report: Problematic social media use and sleep disturbances are longitudinally associated with depressive symptoms in adolescents. *Journal of Adolescence*, *76*(September), 197–201. https://doi.org/10.1016/j.adolescence.2019.09.005

Raudsepp, L., & Kais, K. (2019). Longitudinal associations between problematic social media use and depressive symptoms in adolescent girls. *Preventive Medicine Reports*, *15*(June), 100925. https://doi.org/10.1016/j.pmedr.2019.100925

Ravens-Sieberer, U., Erhart, M., Torsheim, T., Hetland, J., Freeman, J., Danielson, M., Thomas, C., Alexandrova, B., Morgan, A., Lepp, K., Välimäa, R., Vignes, C., Haehne, C., Nickel, J., Helle, N., Schnohr, C., Kökönyei, G., Cavallo, F., Gobina, I., … Overpeck, M. (2008). An international scoring system for self-reported health complaints in adolescents. *European Journal of Public Health*, *18*(3), 294–299. https://doi.org/10.1093/eurpub/ckn001

Reinecke, J. (2006a). Longitudinal analysis of adolescents' deviant and delinquent behavior: Applications of latent class growth curves and growth mixture models. *Methodology*, *2*(3), 100–112. https://doi.org/10.1027/1614-2241.2.3.100

Reinecke, J. (2006b). The development of deviant and delinquent behavior of adolescents: Applications of latent class growth curves and growth mixture models. *Longitudinal Models in the Behavioral and Related Sciences*, *3*(1), 239–266. https://doi.org/10.4324/9781315091655-10

Reiter, J. P., Raghunathan, T. E., & Kinney, S. K. (2006). The importance of modeling the sampling design in multiple imputation for missing data. *Survey Methodology*, *32*(2), 143149.

Rhee, S. H., Friedman, N. P., Boeldt, D. L., Corley, R. P., Hewitt, J. K., Knafo, A., Lahey, B. B., Robinson, J., Van Hulle, C. A., Waldman, I. D., Young, S. E., & Zahn-Waxler, C. (2013). Early concern and disregard for others as predictors of antisocial behavior. *Journal of Child Psychology and Psychiatry and Allied Disciplines*, *54*(2), 157–166. https://doi.org/10.1111/j.1469-7610.2012.02574.x

Rhemtulla, M., Brosseau-Liard, P. É., & Savalei, V. (2012). When can categorical variables be treated as continuous? A comparison of robust continuous and categorical SEM estimation methods under suboptimal conditions. *Psychological Methods*, *17*(3), 354–373. https://doi.org/10.1037/a0029315

Rhodes, L., & Orlowski, J. (2020). *The social dilemma [Video file]*. https://www.netflix.com/nl/title/81254224

Richards, D., Caldwell, P. H. Y., & Go, H. (2015). Impact of social media on the health of children and young people. *Journal of Paediatrics and Child Health*, *51*(12), 1152–1157. https://doi.org/10.1111/jpc.13023

Riehm, K. E., Feder, K. A., Tormohlen, K. N., Crum, R. M., Young, A. S., Green, K. M., Pacek, L. R., La Flair, L. N., & Mojtabai, R. (2019). Associations between time spent using social media and internalizing and externalizing problems among US youth. *JAMA Psychiatry*, *21205*(12), 1266–1273. https://doi.org/10.1001/jamapsychiatry.2019.2325

Roberts, C., Currie, C., Samdal, O., Currie, D., Smith, R., & Maes, L. (2007). Measuring the health and health behaviours of adolescents through cross-national survey research: Recent developments in the Health Behaviour in School-aged Children (HBSC) study. *Journal of Public Health*, *15*(3), 179–186. https://doi.org/10.1007/s10389-007-0100-x

Roeder, K. M., Martin, N. C., Nick, E., Cole, D. A., Spinelli, T., Zelkowitz, R. L., & Sinclair-McBride, K. (2016). Longitudinal and incremental relation of cybervictimization to negative self-cognitions and depressive dymptoms in young adolescents. *Journal of Abnormal Child Psychology*, *44*(7), 1321–1332. https://doi.org/10.1007/s10802-015-0123-7

Rømer Thomsen, K., Buhl Callesen, M., Hesse, M., Lehmann Kvamme, T., Mulbjerg Pedersen, M., Uffe Pedersen, M., & Voon, V. (2018). Impulsivity traits and addiction-related behaviors in youth. *Journal of Behavioral Addictions*, *7*(2), 317–330. https://doi.org/10.1556/2006.7.2018.22

Rose, C. A., & Tynes, B. M. (2015). Longitudinal associations between cybervictimization and mental health among U.S. adolescents. *Journal of Adolescent Health*, *57*(3), 305–312. https://doi.org/10.1016/j.jadohealth.2015.05.002

Rose, E., Hands, B., & Larkin, D. (2012). Reliability and validity of the self-perception profile for adolescents: An Australian sample. *Australian Journal of Psychology*, *64*(2), 92–99. https://doi.org/10.1111/j.1742-9536.2011.00031.x

Rosen, L. D., Whaling, K., Carrier, L. M., Cheever, N. A., & Rokkum, J. (2013). The media and technology usage and attitudes scale: An empirical investigation. *Computers in Human Behavior*, *29*(6), 2501–2511. https://doi.org/10.1016/j.chb.2013.06.006

Rosenberg. (1965). Rosenberg self-esteem scale (RSE). In J. Ciarrochi & L. Bilich (Eds.), *Acceptance and commitment therapy. Measures package* (pp. 61–62). University of Wollongong. http://www.integrativehealthpartners.org/downloads/ACTmeasures.pdf

Royston, P., & White, I. R. (2011). Multiple Imputation by Chained Equations (MICE): Implementation in Stata. *Journal of Statistical Software*, *45*(4), 1–20. https://doi.org/10.18637/jss.v045.i04

RStudio Team. (2021). *RStudio: Integrated Development Environment for R*. RStudio, PBC, Boston, MA. http://www.rstudio.com/

Ryan, T., & Xenos, S. (2011). Who uses Facebook? An investigation into the relationship between the Big Five, shyness, narcissism, loneliness, and Facebook usage. *Computers in Human Behavior*, *27*(5), 1658–1664. https://doi.org/10.1016/j.chb.2011.02.004

Saha, T. D., Chou, S. P., & Grant, B. F. (2006). Toward an alcohol use disorder continuum using item response theory: Results from the National Epidemiologic Survey on Alcohol and Related Conditions. *Psychological Medicine*, *36*(7), 931–941. https://doi.org/10.1017/S003329170600746X

Şahin, C. (2018). Social Media Addiction Scale-student form: The reliability and validity study. *Tojet - The Turkish Online Journal of Educational Technology*, *17*(1), 169–182.

Salmela-Aro, K., Upadyaya, K., Hakkarainen, K., Lonka, K., & Alho, K. (2017). The dark side of internet use: Two longitudinal studies of excessive internet use, depressive symptoms, school burnout and engagement among Finnish early and late adolescents. *Journal of Youth and Adolescence*, *46*(2), 343–357. https://doi.org/10.1007/s10964-016-0494-2

Sampasa-Kanyinga, H., & Hamilton, H. A. (2015). Use of social networking sites and risk of cyberbullying victimization: A population-level study of adolescents. *Cyberpsychology, Behavior, and Social Networking*, *18*(12), 704–710. https://doi.org/10.1089/cyber.2015.0145

Sass, D. A., Schmitt, T. A., & Marsh, H. W. (2014). Evaluating model fit with ordered categorical data within a measurement invariance framework: A comparison of estimators. *Structural Equation Modeling*, *21*(2), 167–180. https://doi.org/10.1080/10705511.2014.882658

Savci, M., Ercengiz, M., & Aysan, F. (2018). Turkish adaptation of Social Media Disorder Scale in adolescents. *Archives of Neuropsychiatry*, *55*(3), 248–255. https://doi.org/10.5152/npa.2017.19285

Schemer, C., Masur, P. K., Geiß, S., & Mu, P. (2020). The impact of Internet and social media use on well-being: A longitudinal analysis of adolescents across nine years. *Journal of Computer-Mediated Communication*, *00*, 1–21. https://doi.org/10.1093/jcmc/zmaa014

Schermelleh-Engel, K., Moosbrugger, H., & Müller, H. (2003). Evaluating the fit of structural equation models: Tests of significance and descriptive goodness-of-fit measures. *Methods of Psychological Research Online*, *8*(2), 23–74. https://doi.org/10.1002/0470010940

Schiltkamp, J. (2021). The effectiveness of the online module "Je Smartphone de Baas" among Dutch university students in reducing smartphone use. *Masterthesis*.

Schmidt, A. F., & Finan, C. (2018). Linear regression and the normality assumption. *Journal of Clinical Epidemiology*, *98*, 146–151. https://doi.org/10.1016/j.jclinepi.2017.12.006

Scholte, E., & Van der Ploeg, J. (1999). De ontwikkeling en toetsing van de ADHD-vragenlijst. *Kind En Adolescent*, *20*(2), 50–60. https://doi.org/10.1007/BF03060728

Shensa, A., Escobar-Viera, C. G., Sidani, J. E., Bowman, N. D., Marshal, M. P., & Primack, B. A. (2017). Problematic social media use and depressive symptoms among U.S. young adults: A nationally-representative study. *Social Science and Medicine*, *182*, 150–157. https://doi.org/10.1016/j.socscimed.2017.03.061

Smahel, D., Machackova, H., Mascheroni, G., Dedkova, L., Staksrud, E., Ólafsson, K., Livingstone, S., & Hasebrink, U. (2020). *EU Kids Online 2020: Survey results from 19 countries*. https://doi.org/10.21953/lse.47fdeqj01ofo

Soldz, S. (2002). *MINAP: Stata module to calculate minimum average partial correlation for principal components*. Boston College Department of Economics. http://fmwww.bc.edu/repec/bocode/m/minap.ado

Starcevic, V., Billieux, J., & Schimmenti, A. (2018). Selfitis, selfie addiction, Twitteritis: Irresistible appeal of medical terminology for problematic behaviours in the digital age. *Australian & New Zealand Journal of Psychiatry*, *52*(5), 408–409. https://doi.org/10.1177/0004867418763532

StataCorp. (2013). *Stata Statistical Software: Release 13*. StataCorp LP.

StataCorp. (2015). *Stata Statistical Software: Release 14*. StataCorp LP.

Stavrova, O., & Denissen, J. (2020). Does using social media jeopardize well-being? The importance of separating within- from between-person effects. *Social Psychological and Personality Science*. https://doi.org/10.1177/1948550620944304

Steinberg, L., & Morris, A. S. (2001). Adolescent development. *Annual Review of Clinical Psychology*, *52*, 83–110. https://doi.org/10.1146/annurev.psych.52.1.83

Stevens, G. W. J. M., Van Dorsselaer, S. A. F. M., Boer, M., De Roos, S. A., Duinhof, E. L., Ter Bogt, T. F. M., Van den Eijnden, R. J. J. M., Kuyper, L. S., Visser, D. M., Vollebergh, W. A. M., & De Looze, M. E. (2018). *HBSC 2017: Gezondheid en welzijn van jongeren in Nederland [Health behavior in school-aged children in the Netherlands]*. Utrecht University.

Stoel, R. D., Garre, F. G., Dolan, C., & Van den Wittenboer, G. (2006). On the likelihood ratio test in structural equation modeling when parameters are subject to boundary constraints. *Psychological Methods*, *11*(4), 439–455. https://doi.org/10.1037/1082-989X.11.4.439

Straathof, M. A. E., & Treffers, P. D. (1989). *De adolescenten-versie van de CBSK*. Academisch Centrum Kinder-en Jeugdpsychiatrie Curium.

Sullivan, G. M., & Feinn, R. (2012). Using effect size—or why the P value is not enough. *Journal of Graduate Medical Education*, *4*(3), 279–282. https://doi.org/10.4300/jgme-d-12-00156.1

Sumter, S. R., Valkenburg, P. M., Baumgartner, S. E., Peter, J., & Van der Hof, S. (2015). Development and validation of the Multidimensional Offline and Online Peer Victimization Scale. *Computers in Human Behavior*, *46*, 114–122. https://doi.org/10.1016/j.chb.2014.12.042

Sun, Y., & Zhang, Y. (2021). A review of theories and models applied in studies of social media addiction and implications for future research. *Addictive Behaviors*, *114*, 106699. https://doi.org/10.1016/j.addbeh.2020.106699

Sznitman, S. R., Kolobov, T., ter Bogt, T., Kuntsche, E., Walsh, S. D., & Harel-Fisch, Y. (2015). Investigating cannabis use normalization by distinguishing between experimental and regular Use: A multilevel study in 31 countries. *Journal of Studies on Alcohol and Drugs*, *76*(2), 181–189. https://doi.org/10.15288/jsad.2015.76.181

Tang, S., Werner-Seidler, A., Torok, M., Mackinnon, A. J., & Christensen, H. (2021). The relationship between screen time and mental health in young people: A systematic review of longitudinal studies. *Clinical Psychology Review*, *86*, 102021. https://doi.org/10.1016/j.cpr.2021.102021

Throuvala, M. A., Gri, M. D., Rennoldson, M., & Kuss, D. J. (2020). Mind over matter: Testing the efficacy of an online randomized controlled trial to reduce distraction from smartphone use. *International Journal of Environmental Research and Public Health*, *17*(13), 4842. https://doi.org/10.3390/ijerph17134842

Toland, M. D. (2014). Practical guide to conducting an Item Response Theory analysis. *Journal of Early Adolescence*, *34*(1), 120–151. https://doi.org/10.1177/0272431613511332

Torsheim, T., & Wold, B. (2001). School-related stress, school support, and somatic complaints: A general population study. *Journal of Adolescent Research*, *16*(3), 293–303.

Trimbos-institute. (2020). *Digital balance*. www.digitalebalans.nl

Twenge, J. M. (2019). More time on technology, less happiness? Associations between digital-media use and psychological well-being. *Current Directions in Psychological Science*, *28*(4), 372–379. https://doi.org/10.1177/0963721419838244

Twenge, J. M., & Campbell, W. K. (2018). Associations between screen time and lower psychological well-being among children and adolescents: Evidence from a population-based study. *Preventive Medicine Reports*, *12*, 271–283. https://doi.org/10.1016/j.pmedr.2018.10.003

Twenge, J. M., Joiner, T., Rogers, M., & Martin, G. (2018). Increases in depressive symptoms, suicide-related outcomes, and suicide rates among U.S. adolescents after 2010 and links to increased new media screen time. *Clinical Psychological Science 2018*, *6*(1), 3–17. https://doi.org/10.1177/2167702617723376

Twenge, J. M., Martin, G. N., & Campbel, W. K. (2018). Decreases in psychological well-being among American adolescents. *Emotion*, *18*(6), 765–780. https://doi.org/10.1037/emo0000403

Uebersax, J. S. (1999). Probit latent class analysis with dichotomous or ordered category measures: Conditional independence/dependence models. *Applied Psychological Measurement*, *23*(4), 283–297. https://doi.org/10.1177/01466219922031400

Underwood, M. K., & Ehrenreich, S. E. (2017). The power and the pain of adolescents' digital communication: Cyber victimization and the perils of lurking. *American Psychologist*, *72*(2), 144–158. https://doi.org/10.1037/a0040429

Unicef. (2017). State of the worlds children 2017: Children in a digital world. In *Unicef*.

Valkenburg, P. M., Beyens, I., Pouwels, J. L., & Van Driel, I. I. (2021). Social media browsing and adolescent well-being: Challenging the "Passive Social Media Use Hypothesis." *Preprint*. https://doi.org/10.31234/osf.io/gzu3y

Valkenburg, P. M., & Peter, J. (2007). Online communication and adolescent well-being: Testing the stimulation versus the displacement hypothesis. *Journal of Computer-Mediated Communication*, *12*(4), 1169–1182. https://doi.org/10.1111/j.1083-6101.2007.00368.x

Valkenburg, P. M., & Peter, J. (2009). Social consequences of the Internet for adolescents: A decade of research. *Current Directions in Psychological Science*, *18*(1), 1–5. https://doi.org/10.1111/j.1467-8721.2009.01595.x

Valkenburg, P. M., & Peter, J. (2011). Online communication among adolescents: An integrated model of its attraction, opportunities, and risks. *Journal of Adolescent Health*, *48*(2), 121–127. https://doi.org/10.1016/j.jadohealth.2010.08.020

Valkenburg, P. M., & Peter, J. (2013). The differential susceptibility to media effects model. *Journal of Communication*, *63*(2), 221–243. https://doi.org/10.1111/jcom.12024

Valkenburg, P. M., Pouwels, J. L., Beyens, I., Van Driel, I. I., & Keijsers, L. (2021). Adolescents' social media experiences and their self-esteem: A person-specific susceptibility perspective. *Technology, Mind, and Behavior*, *2*(2), 1–34. https://doi.org/10.1037/tmb0000037

Valkenburg, P. M., Van Driel, I. I., & Beyens, I. (2021). Social media and well-being: Time to abandon the active-passive dichotomy. *Preprint*. https://doi.org/10.31234/osf.io/j6xqz

Van de Schoot, R., Lugtig, P., & Hox, J. (2012). A checklist for testing measurement invariance. *European Journal of Developmental Psychology*, *9*(4), 486–492. https://doi.org/10.1080/17405629.2012.686740

Van de Schoot, R., Sijbrandij, M., Winter, S. D., Depaoli, S., & Vermunt, J. K. (2017). The GRoLTS-Checklist: Guidelines for reporting on latent trajectory studies. *Structural Equation Modeling*, *24*(3), 451–467. https://doi.org/10.1080/10705511.2016.1247646

Van den Brink, W. (2017). ICD-11 Gaming Disorder: Needed and just in time or dangerous and much too early? *Journal of Behavioral Addictions*, *6*(3), 290–292. https://doi.org/10.1556/2006.6.2017.040

Van den Eijnden, R. J. J. M., Koning, I. M., Doornwaard, S. M., Van Gurp, F., & Ter Bogt, T. F. M. (2018). The impact of heavy and disordered use of games and social media on adolescents' psychological, social, and school functioning. *Journal of Behavioral Addictions*, *7*(3), 697–706. https://doi.org/10.1556/2006.7.2018.65

Van den Eijnden, R. J. J. M., Lemmens, J. S., & Valkenburg, P. M. (2016). The Social Media Disorder Scale: Validity and psychometric properties. *Computers in Human Behavior*, *61*, 478–487. https://doi.org/10.1016/j.chb.2016.03.038

Van den Eijnden, R. J. J. M., Vermulst, A., Van Rooij, A. J., Scholte, R., & Van de Mheen, D. (2014). The bidirectional relationships between online victimization and psychosocial problems in adolescents: A comparison with real-life victimization. *Journal of Youth and Adolescence*, *43*(5), 790–802. https://doi.org/10.1007/s10964-013-0003-9

Van der Schuur, W. A., Baumgartner, S. E., Sumter, S. R., & Valkenburg, P. M. (2018). Media multitasking and sleep problems: A longitudinal study among adolescents. *Computers in Human Behavior*, *81*, 316–324. https://doi.org/10.1016/j.chb.2017.12.024

Van Dorsselaer, S. A. F. M. (2018). Methode van onderzoek en beschrijving van de steekproef [Methods and sample description]. In G. W. J. M. Stevens, S. A. F. M. Van Dorsselaer, M. Boer, S. A. De Roos, E. L. Duinhof, T. F. M. Ter Bogt, R. J. J. M. Van den Eijnden, L. S. Kuyper, D. M. Visser, W. A. M. Vollebergh, & M. E. De Looze (Eds.), *HBSC 2017: Gezondheid en welzijn van jongeren in Nederland [Health behavior in school-aged children in the Netherlands]* (pp. 13–27). Utrecht University.

Van Huijstee, M., Nieuwenhuizen, W., Sanders, M., Masson, E., & Boheemen, P. van. (2021). *Online ontspoord [Losing track online]*. Rathenau Instituut.

Van Rooij, A. J., Ferguson, C. J., Carras, M. C., Kardefelt-Winther, D., Shi, J., Aarseth, E., Bean, A. M., Bergmark, K. H., Brus, A., Coulson, M., Deleuze, J., Dullur, P., Dunkels, E., Edman, J., Elson, M., Etchells, P. J., Fiskaali, A., Granic, I., Jansz, J., … Przybylski, A. K. (2018). A weak scientific basis for gaming disorder: Let us err on the side of caution. *Journal of Behavioral Addictions*, *7*(1), 1–9. https://doi.org/10.1556/2006.7.2018.19

Van Rooij, A. J., Kuss, D. J., Griffiths, M. D., Shorter, G. W., Schoenmakers, T. M., & Van De Mheen, D. (2014). The (co-)occurrence of problematic video gaming, substance use, and psychosocial problems in adolescents. *Journal of Behavioral Addictions*, *3*(3), 157–165. https://doi.org/10.1556/JBA.3.2014.013

Van Rooij, A. J., & Prause, N. (2014). A critical review of "internet addiction" criteria with suggestions for the future. *Journal of Behavioral Addictions*, *3*(4), 203–213. https://doi.org/10.1556/JBA.3.2014.4.1

Vangeel, J., De Cock, R., Klein, A., Minotte, P., Rosas, O., & Meerkerk, G. J. (2016). Compulsive use of social networking sites among secondary school adolescents in Belgium. In M. Walrave, K. Ponnet, E. Vanderhoven, J. Haers, & B. Segaert (Eds.), *Youth 2.0: Social Media and Adolescence* (pp. 179–191). Springer. https://doi.org/10.1007/978-3-319-27893-3

Vannucci, A., & McCauley Ohannessian, C. (2019). Social media use subgroups differentially predict psychosocial well-being during early adolescence. *Journal of Youth and Adolescence*, 1469–1493. https://doi.org/10.1007/s10964-019-01060-9

Veissière, S. P. L., & Stendel, M. (2018). Hypernatural monitoring: A social rehearsal account of smartphone addiction. *Frontiers in Psychology*, *9*(141), 1–10. https://doi.org/10.3389/fpsyg.2018.00141

Velicer, W. F. (1976). Determining the number of components from the matrix of partial correlations. *Psychometrika*, *41*(3), 321–327. https://doi.org/10.1007/BF02293557

Verduyn, P., Gugushvili, N., Massar, K., Täht, K., & Kross, E. (2020). Social comparison on social networking sites. *Current Opinion in Psychology*, *36*, 32–37. https://doi.org/10.1016/j.copsyc.2020.04.002

Verduyn, P., Lee, D. S., Park, J., Shablack, H., Orvell, A., Bayer, J., Ybarra, O., Jonides, J., & Kross, E. (2015). Passive facebook usage undermines affective well-being: Experimental and longitudinal evidence. *Journal of Experimental Psychology: General*, *144*(2), 480–488. https://doi.org/10.1037/xge0000057

Verduyn, P., Ybarra, O., Résibois, M., Jonides, J., & Kross, E. (2017). Do social network sites enhance or undermine subjective well-being? A critical review. *Social Issues and Policy Review*, *11*(1), 274–302. https://doi.org/10.1111/sipr.12033

Wallsten, S. (2013). *What we are not doing when we're online*. National Bureau of Economic Research. https://doi.org/10.3386/w19549

Wang, L. P., & Maxwell, S. E. (2015). On disaggregating between-person and within-person effects with longitudinal data using multilevel models. *Psychological Methods*, *20*(1), 63–83. https://doi.org/10.1037/met0000030

Wartberg, L., Kriston, L., & Thomasius, R. (2020). Internet gaming disorder and problematic social media use in a representative sample of German adolescents: Prevalence estimates, comorbid depressive symptoms and related psychosocial aspects. *Computers in Human Behavior*, *103*, 31–36. https://doi.org/10.1016/j.chb.2019.09.014

Watson, J. C., Prosek, E. A., & Giordano, A. L. (2020). Investigating psychometric properties of social media addiction measures among adolescents. *Journal of Counseling and Development*, *98*(4), 458–466. https://doi.org/10.1002/jcad.12347

Weber, M., Ziegele, M., & Schnauber, A. (2013). Blaming the victim: The effects of extraversion and information disclosure on guilt attributions in cyberbullying. *Cyberpsychology, Behavior, and Social Networking*, *16*(4), 254–259. https://doi.org/10.1089/cyber.2012.0328

Wenninger, H., Krasnova, H., & Buxmann, P. (2014). Activity matters: Investigating the influence of Facebook on life satisfaction of teenage users. *Proceedings of the European Conference on Information Systems (ECIS)*.

Werning, S. (2017). Ethical implications of affordance change in contemporary social media platforms. *Communication and Culture Review*, *1*(1), 15–32. https://doi.org/10.13140/RG.2.2.18419.22568

Wiederhold, B. K. (2019). Does digital media use increase symptoms of ADHD in adolescents? *Cyberpsychology, Behavior, and Social Networking*, *22*(3), 171–172. https://doi.org/10.1089/cyber.2019.29143.bkw

Wilens, T. E. (2004). Impact of ADHD and its treatment on substance abuse in adults. *Journal of Clinical Psychiatry*, *65*(SUPPL. 3), 38–45.

Williams, R. (2012). Using the margins command to estimate and interpret adjusted predictions and marginal effects. *Stata Journal*, *12*(2), 308–331. https://doi.org/10.1177/1536867x1201200209

Wirtz, D., Tucker, A., Briggs, C., & Schoemann, A. M. (2020). How and why social media affect subjective well-being: Multi-site use and social comparison as predictors of change across time. *Journal of Happiness Studies*, *22*(4), 1673–1691. https://doi.org/10.1007/s10902-020-00291-z

Wong, H. Y., Mo, H. Y., Potenza, M. N., Chan, M. N. M., Lau, W. M., Chui, T. K., Pakpour, A. H., & Lin, C. Y. (2020). Relationships between severity of internet gaming disorder, severity of problematic social media use, sleep quality and psychological distress. *International Journal of Environmental Research and Public Health*, *17*(6), 1–13. https://doi.org/10.3390/ijerph17061879

World Health Organization. (2019). 06: Mental, behavioural or neurodevelopmental disorders: Disorders due to substance use or addictive behaviors: Disorders due to addictive behaviours. In World Health Organization (Ed.), *International classification of diseases for mortality and morbidity statistics (11th Revision)*. https://icd.who.int

Wu, A., Cheung, V., Ku, L., & Hung, E. (2013). Psychological risk factors of addiction to social networking sites among Chinese smartphone users. *Journal of Behavioral Addictions*, *2*(3), 160–166. https://doi.org/10.1556/JBA.2.2013.006

Yang, C. C. (2016). Instagram use, loneliness, and social comparison orientation: Interact and browse on social media, but don't compare. *Cyberpsychology, Behavior, and Social Networking*, *19*(12), 703–708. https://doi.org/10.1089/cyber.2016.0201

Yardi, S., & Bruckman, A. (2011). Social and technical challenges in parenting teens' social media use. *Conference on Human Factors in Computing Systems - Proceedings*, 3237–3246. https://doi.org/10.1145/1978942.1979422

Zimet, G. D., Dahlem, N. W., Zimet, S. G., & Farley, G. K. (1988). The multidimensional scale of perceived social support. *Journal of Personality Assessment*, *51*(1), 30–41.

# Dankwoord

[ACKNOWLEDGEMENTS]

# Dankwoord

De afgelopen jaren heb ik mij onwijs ondersteund gevoeld door mijn promotoren, collega's, vrienden en familie. Mede dankzij hen is dit proefschrift tot stand gekomen.

Als eerste wil ik mijn promotoren bedanken. **Gonneke**, **Regina** en **Catrin**, wat ben ik blij met jullie begeleiding van de afgelopen vier jaar. Jullie gaven mij de ruimte om mijn ideeën uit te werken, maar waren ook altijd kritisch op mijn suggesties en uitwerkingen daarvan. Hier heb ik ontzettend veel van geleerd. Ook hebben jullie me altijd veel vertrouwen gegeven en hierdoor heb ik meer vertrouwen in mezelf gekregen als onderzoeker. Ik moest af en toe wel even slikken na het lezen van de anonieme reviews op onze artikelen. Terwijl ik na het lezen van deze reviews een resubmissie soms somber inzag, bleven jullie altijd positief en bemoedigend. Dit heeft mij ontzettend geholpen tijdens het publicatieproces. Daarnaast wil ik jullie bedanken voor jullie flexibiliteit: de laatste paar maanden moest er nog veel gedaan worden en deed ik daarom veel beroep op jullie. Echt fijn dat ik zo vaak op jullie feedback kon rekenen. Bovendien hebben jullie me niet alleen super ondersteund op werkgebied, maar ook persoonlijk. **Gonneke**, ik wil je niet alleen bedanken voor je fantastische begeleiding bij mijn PhD, maar ook voor de kansen die je me hebt gegeven de afgelopen jaren daarbuiten, zoals het meewerken aan jouw internationale artikelen, de gave HBSC-gerelateerde projecten waar je me bij betrokken hebt en natuurlijk mijn huidige postdoc functie. Ik vind het heel fijn om met je samen te werken. Als ik me bijvoorbeeld ergens zorgen over maak, dan kan jij altijd zo goed relativeren en me daarmee gerust stellen: het komt uiteindelijk toch altijd goed! **Regina**, ik heb ontzettend veel gehad aan jouw kennis en expertise op het gebied van het onderwerp van dit proefschrift. Hier heb ik een groot deel van mijn inspiratie vandaan gehaald en hiermee heb je mij veel nieuwe inzichten gegeven. Bovendien vind ik het fijn dat je zo pragmatisch kunt zijn. Als ik ergens lang mee worstelde of vastliep bij het maken van keuzes of bij het schrijven, dan doorzag je dit vaak en kon je mij goed helpen met het vinden van een oplossing. **Catrin**, ik vind jou zo ongelofelijk scherp. Als ik iets zei over een klein detail in een van onze artikelen, dan wist je altijd meteen waar ik het over had. Bovendien heb ik heel veel gehad aan jouw feedback, dat je altijd uitvoerig gaf zowel op overkoepelend- als op detailniveau. Hier heb ik heel veel van geleerd en veel van jouw feedback neem ik mee in mijn toekomstige onderzoek. Ook vind ik je gewoon een heel fijn persoon. Je straalt zoveel enthousiasme uit en toont veel betrokkenheid. Dat waardeer ik heel erg!

Bedankt PhD/Fabulinus collega's van Jeugdstudies (Dom, Shanshan, Elisa, Lydia, Suzanne, Heiko, Ties, Yanyu, Ying, Hilde) en daarbuiten (Sandra, Evi, Wybren, Tom, Nora, Janna) voor jullie gezelligheid tijdens het werken. **Dom**, since we both started our PhD at the same time, we underwent comparable processes. It was really nice to talk to you from time to time about our shared experiences; that meant a lot to me. Furthermore, you have played an important role in connecting us PhD's in times of corona. I am grateful for your initiative to have regular online Fabulinus meetings, which I really enjoyed. Also, thank you for helping me out in the last few months with all my questions around submitting the dissertation and preparing for the defense; your information was extremely helpful. **Shanshan**, thank you for all our good chats. It is such a great pleasure to have you as a colleague. Not only are you really funny, you are also very generous, for example by sharing the most delicious chocolates, which are impossible to resist. Also big thanks for your major role in organizing the online birthday meetings within our group. Those moments where we sang happy birthday behind our screens were one of my favorite (though really challenging)! I also really enjoyed our dumpling evenings: thank you for your hospitality. **Elisa** en **Lydia**, ik heb jullie echt gemist tijdens mijn laatste jaar! Bedankt voor jullie gezelligheid op onze werkkamer in het Langeveldgebouw en de leuke koffie- en lunchpauzes daarbuiten. **Sandra**, wat is het fijn om zo'n vrolijke en betrokken collega te hebben zoals jij. Al snel voelde ik een goede klik met jou. Hoe kan het ook anders, want je bent een van de meest sociale personen die ik ken. Ook bedankt voor jouw feedback op de introductie van mijn proefschrift. **Evi**, het was super fijn om in tijden van lockdown tijdens het werken samen regelmatig een frisse neus te halen in onze oude fantastische wijk Lombok.

Daarnaast wil ik ook mijn andere **collega's van onze afdeling Jeugdstudies** bedanken (Ina, Margreet, Margot, Tom, Marlies, Wilma, Vincent, Marloes, Luzia, Gaëlle, Manja, Gerdien). Het is me een groot genoegen om te werken bij een groep met een brede expertise, waar inspirerend onderzoek wordt gedaan en waar bovendien de sfeer heel positief en open is. Ook bedankt **collega's van het secretariaat en management** voor al jullie praktische ondersteuning de afgelopen jaren (Wil, Nelly, Sophie, Marscha, Monique, Magda).

Er zijn ook andere mensen binnen de UU die ik wil bedanken. **Collega's van de afdeling Methoden & Statistiek**, wat fijn dat er zo veel expertise is op het gebied van geavanceerde statistiek binnen onze faculteit. Bedankt voor de ondersteuning bij al mijn vragen over mijn analyses. Ook wil ik graag de **docenten van mijn masterstudie** Sociology and Social Research bedanken, in het bijzonder Frank van Tubergen en Jeroen Weesie. **Frank**, bedankt voor de fijne begeleiding bij mijn scriptie en het helpen publiceren ervan. Hierdoor heb ik voordat ik mijn PhD begon al ervaring op kunnen doen met het schrijven van een wetenschappelijk artikel en publiceren, wat me erg heeft geholpen tijdens de beginfase van mijn PhD. **Jeroen**, ik heb onwijs veel geleerd van jouw statistiek cursussen. Hierdoor had ik een goede basis voor mijn PhD die onmisbaar is geweest voor het kunnen uitvoeren van mijn analyses. Ook heb ik veel gehad aan al jouw extra lesmateriaal van de cursussen: deze heb ik regelmatig geraadpleegd wanneer ik informatie zocht over specifieke methoden.

In het eerste jaar van mijn PhD (2017/2018) werkte ik op het Trimbos-instituut om bij te dragen aan de dataverzameling van het HBSC onderzoek. **Saskia**, bedankt voor de samenwerking in die tijd. Met jouw jarenlange ervaring in het coördineren van data verzamelen ben je altijd één stap voor in het voorzien van obstakels en mede daardoor loopt de HBSC dataverzameling altijd gesmeerd. Ik heb ontzettend veel van je geleerd.

During my PhD I also had the opportunity to work with **international colleagues from the HBSC network**. It is a great pleasure to be part of the "HBSC family" and I look forward to meeting many of you in person. Special thanks to **Alina**, you have learned me so much about the network and made me feel so welcome within the Early Careers Group. It was also a great pleasure to have you as a colleague at the UU, which allowed me to get to know you even better. I would also like to thank **Meyran** and **Jo** for the nice collaboration on our HBSC papers and for providing me the opportunity to contribute to the HBSC network, for example by involving me in the protocol work.

Ik wil ook de beoordelingscommissie **prof. dr. Valkenburg**, **prof. dr. Keijsers**, **prof. dr. Kleinjan**, **prof. dr. ter Bogt**, en **dr. Peeters** hartelijk bedanken voor het lezen en goedkeuren van dit proefschrift.

Daarnaast zijn er ook mensen in mijn persoonlijke omgeving die ik wil bedanken. Allereerst mijn moeder **Rieke**. Toen ik je in 2014 vertelde dat ik wéér een nieuwe studie wilde doen die mij beter zou voorbereiden op een loopbaan als onderzoeker, twijfelde je geen moment en moedigde je me aan om het te doen. Zonder die extra studie zou ik niet zijn waar ik nu ben. Je geeft me altijd veel vertrouwen in de keuzes die ik maak en daar ben ik je heel dankbaar voor.

Mijn dank gaat ook uit naar mijn schoonouders **Mieke** en **Huib**. Ook jullie hebben bijgedragen aan dit proefschrift. Ik vind het ontzettend leuk dat jullie hebben meegelezen met een aantal van mijn artikelen en ben jullie zeer dankbaar voor het nalezen van de samenvatting van dit proefschrift.

Ook wil ik al mijn lieve vrienden bedanken, waar ik de afgelopen jaren ook zo veel aan heb gehad. Met jullie kan ik lachen, huilen en gewoon echt mezelf zijn. Van jullie krijg ik onwijs veel energie. Ik ben super dankbaar voor jullie vriendschap. In het bijzonder wil ik mijn paranimfen **Anke** en **Suzette** bedanken. Wat ben ik blij met jullie als vriendinnen. Dank voor jullie ondersteuning bij het organiseren van de dag van mijn verdediging. Anke, wist je dat wij dit jaar (2022) al 15 jaar vriendinnen zijn? Binnenkort vieren we dus niet alleen het afronden van dit proefschrift, maar ook ons lustrum! We hebben samen zoveel leuke dingen gedaan: samengewoond, duizenden etentjes, heel veel gefeest, leuke tripjes gemaakt, en nog veel meer! Bedankt daarvoor. Suzette, ook wij kennen elkaar inmiddels heel lang. Door jou voel ik me altijd heel erg gehoord. En wat kan ik hard lachen met jou. Als ik bijvoorbeeld denk aan ons weekendje Antwerpen en dan vooral aan hoe de avond daarvoor was verlopen, dan krijg ik nog steeds een lach op mijn gezicht. Bedankt voor je steun en het lachen van de afgelopen jaren.

Tot slot mijn allerliefsten. Lieve **Camiel**, wat fijn dat je zo lekker tevreden trappelend in mijn buik zat tijdens het laatste negen maanden van mijn PhD. Hier genoot ik ontzettend van en hiermee gaf je me veel kracht voor de laatste loodjes. Lieve **Matthijs**, ondanks dat je niet in dit dankwoord wilde voorkomen, doe ik het toch. Het zou oneerlijk zijn om je hier buiten te laten. Je bent namelijk van onschatbare waarde. Met jou aan mijn zijde is alles zoveel makkelijker en leuker. Jij draagt elke dag bij aan mijn geluk. Ik kijk uit naar onze toekomst. Dikke kus.

# Curriculum Vitae

# About the Author

Maartje Boer (1990) obtained a bachelor in Law at the University of Applied Sciences Utrecht in 2011. In 2014, she obtained her master's degree of the program Social Policy and Interventions at Utrecht University. In 2017, she obtained her second master's degree of the research master program Sociology and Social Research at Utrecht University (*cum laude*). During her studies, she did research internships at several national research institutes, namely Panteia, The National Institute for Family Finance Information (i.e., Nibud), and the Netherlands Institute for Social Research (i.e., Sociaal and Cultureel Planbureau). Also, she combined here studies with part-time work as a research-assistant at Utrecht University.

In 2017, Maartje started her PhD-project at the department of Interdisciplinary Social Science of Utrecht University on the relation between social media use and wellbeing among adolescents, with particular focus on problematic social media use. As part of her PhD-track, in 2017 and 2018, she assisted with the coordination of the data collection of the 'Health Behaviour in School-aged Children' (HBSC) study in the Netherlands, in which 9000 adolescents from primary and secondary schools participated. During her PhD, she presented her work at international conferences, such as the International Conference on Behavioral Addictions (ICBA) and the European Association for Research on Adolescence (EARA) conference. She also gained experience with other aspects of science during her PhD, for example by being member of the PhD-council of the Faculty of Social and Behavioral Sciences as a representative of her PhD-group, by reviewing studies for international journals (e.g., *Computers in Human Behavior*), and by providing guest lectures on her research to students.

Currently, Maartje is employed at the department of Interdisciplinary Social Science as a postdoctoral researcher. She will work on a national report on the health (behaviors) and wellbeing of Dutch adolescents based on recent data from the HBSC-study (2021), as well as other research projects related to adolescents' health and wellbeing.

## Scientific Publications of This Dissertation

**Boer, M.**, Stevens, G. W. J. M., Finkenauer, C., & Van den Eijnden, R. J. J. M. (2022). The complex association between social media use intensity and adolescent wellbeing: A longitudinal investigation of five factors that may affect the association. *Computers in Human Behavior, 128*, 107084. https://doi.org/10.1016/j.chb.2021.107084

**Boer, M.**, Stevens, G. W. J. M., Finkenauer, C., De Looze, M. E., & Van den Eijnden, R. J. J. M. (2021). The course of problematic social media use in young adolescents: A latent class growth analysis. *Child Development (in press)*. https://doi.org/10.1111/cdev.13712

**Boer, M.**, Van den Eijnden, R. J. J. M., Finkenauer, C., Boniel-Nissim, M., Marino, C., Inchley, J., Cosma, A., Paakkari, L., & Stevens, G. W. J. M. (2022). Cross-national validation of the Social Media Disorder-Scale: Findings from adolescents from 44 countries. *Addiction 117*(3). https://doi.org/10.1111/add.15709

**Boer, M.**, Stevens, G. W. J. M., Finkenauer, C., Koning, I. M. , & Van den Eijnden, R. J. J. M. (2021). Validation of the Social Media Disorder-Scale in adolescents: Findings from a large-scale nationally representative sample. *Assessment (in press)*. https://doi.org/10.1177/10731911211027232

**Boer, M.**, Stevens, G. W. J. M., Finkenauer, C., De Looze, M. E., & Van den Eijnden, R. J. J. M. (2021). Social media use intensity, social media use problems, and mental health among adolescents: Investigating directionality and mediating processes. *Computers in Human Behavior*, *116*, 106645. https://doi.org/10.1016/j.chb.2020.106645

**Boer, M.**, Van den Eijnden, R. J. J. M., Boniel-Nissim, M., Wong, S. L., Inchley, J. C., Badura, P., Craig, W. M., Gobina, I., Kleszczewska, D., Klanšček, H. J., & Stevens, G. W. J. M. (2020). Adolescents' intense and problematic social media use and their well-being in 29 countries. *Journal of Adolescent Health*, *66*(6), S89-S99. https://doi.org/10.1016/j.jadohealth.2020.02.014

**Boer, M.**, Stevens, G. W. J. M., Finkenauer, C., & Van den Eijnden, R. J. J. M. (2020). Attention deficit hyperactivity disorder-symptoms, social media use intensity, and social media use problems in adolescents: Investigating directionality. *Child Development 91*(4), e853-865. https://doi.org/10.1177/10731911211027232

## Other Scientific Publications

**Boer, M**., Twenge, J., Cosma, A., Gariepy, G., Inchley, J., Jericek, H, & Stevens, G. W. J. M. (in preparation). Increases in psychological complaints between 2002 and 2018: The role of schoolwork pressure, family structure, internet use, and obesity. In preparation; author order and title may change.

Stevens, G. W. J. M., **Boer, M.,** Walsh, S. D., Delaruelle, K., Kern, M. R. (in preparation). Can national-level migration policies and attitudes toward immigrants alter the immigration-adolescent mental health link? Results from the internationally comparative HBSC study. In preparation; author order and title may change.

Bi, S., Stevens, G. W. J. M., Maes, M., **Boer, M.**, Delaruelle, K., Eriksson, C., Brooks, F. M., Tesler, R., Van der Schuur, W., & Finkenauer, C. (2021). Perceived social support from different sources and adolescent life satisfaction across 42 countries/regions: The moderating role of national-level generalized trust. *Journal of Youth and Adolescence (50)*, 1384-1409. https://doi.org/10.1007/s10964-021-01441-z

Craig, W., Boniel-Nissim, M., King, N., Walsh, S. D., **Boer, M.,** Donnely, P. D., Harel-Fisch, Y., Malinowska-Cieslik, M., de Matos, M. G., Cosma, A., van den Eijnden, R. J. J. M., Vieno, A., Elgar, F. J., Molcho, M., Bjereld, Y., & Pickett, W. (2020). Social media use and cyber-bullying: A cross-national analysis of young people in 42 countries. *Journal of Adolescent Health*, *66*(6), S100-S108. https://doi.org/10.1016/j.jadohealth.2020.03.006

Stevens, G. W. J. M., **Boer, M.**, Titzmann, P. F., Cosma, A. P., & Walsh, S. D. (2020). Immigration status and bullying victimization: Associations across national and school contexts. *Journal of Applied Developmental Psychology*, *66*, 101075. https://doi.org/10.1016/j.appdev.2019.101075

**Boer, M.**, & Van Tubergen, F. A. (2019). Media messages and attitudes toward Muslims and ethnic minorities: A panel study among ethnic majority adolescents in the Netherlands. *Social Science Research*, *83*, 102311. https://doi.org/10.1016/j.ssresearch.2019.06.002

## Non-Scientific Publications

Kleinjan, M., Pieper, I., Stevens, G. W. J. M., Van de Klundert, N., Rombouts, M., **Boer, M**., & Lammers, J. (2020). *Geluk onder druk? Onderzoek naar het mentaal welbevinden van jongeren in Nederland [An investigation of the mental wellbeing of Dutch adolescents]*. UNICEF Netherlands, Den Haag. https://www.unicef.nl/ons-werk/nederland/geluk-onder-druk-een-onderzoek-over-maar-vooral-met-jongeren/professionals

Stevens, G. W. J. M., **Boer, M.**, van Dorsselaer, S. A. F. M., de Looze, M. E., de Roos, S., ter Bogt, T. F. M., van den Eijnden, R. J. J. M., & Vollebergh, W. A. M. (2020). *Gezondheid en welzijn van Nederlandse jongeren in internationaal perspectief [The health behaviors of Dutch adolescents from an international perspective]*. Utrecht University, Netherlands. http://www.hbsc.org/membership/countries/netherlands.html

**Boer, M.**, & Van den Eijnden, R. J. J. M. (2018). Sociale media en gamen [Social media and gaming]. In G. W. J. M. Stevens, S. A. F. M. Van Dorsselaer, **M. Boer**, S. A. De Roos, E. L. Duinhof, T. F. M. Ter Bogt, R. J. J. M. Van den Eijnden, L. S. Kuyper, D. M. Visser, W. A. M. Vollebergh, & M. E. De Looze (Eds.), HBSC 2017: *Gezondheid en welzijn van jongeren in Nederland* [Health behavior in school-aged children in the Netherlands] (pp. 135–147). Utrecht University, Netherlands. http://www.hbsc.org/membership/countries/netherlands.html