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Socia media use in adolescence: Longitudinal relationships with social functioning and psychopathology

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Social Media Use in Adolescence:

Longitudinal Relationships with Social Functioning and Psychopathology

by

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Dedication

To my mentors, friends, family, and partner;

to those who believed in me when self-belief was *just* out of reach.

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Abstract

Social media use and psychopathology are both prevalent during adolescence; however, the relationship between these two variables is not yet fully understood. Research on these topics is generally myopic in that it focuses on a brief window of time (e.g., cross-sectional studies), a small number of variables (e.g., hours spent per day; depressive symptoms), and uses single reporters and measures (e.g., adolescent report using a questionnaire). Extant literature shows moderate relationships between frequency of social media use and depressive symptoms; however, most studies do not use statistical methods that investigate bidirectionality or parse apart between-person and within-person effects, so effects may be overestimated and misunderstood. Additionally, research on other areas of functioning such as relationships, that may impact (or be impacted by) social media use is still in its infancy. Given these limitations, the current study investigated within-person relationships between two features of social media use (frequency and addictive use), two types of social functioning (prosocial behavior and family conflict), and two types of psychopathology (internalizing and externalizing symptoms) in a nationally representative American sample (Adolescent Brain Cognitive Development study). Random intercept cross-lagged panel models were used to provide clarity on directionality and within-person development. Results showed that social media variables were generally unidirectionally related to other variables. Specifically, higher social media frequency predicted more family conflict and symptoms of psychopathology. An exception to this was prosocial behavior, which predicted more frequent social media use. Social media addiction was generally related to worse outcomes, including less prosocial behavior. This study clarified longitudinal links between these variables at a within-person level and further elucidated differences between high frequency social media use and potentially addictive use.

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Chapter 1: Background

Introduction

Since the inception of social media (SM), developmental psychologists and scientists from other fields have researched how social media use (SMU) might negatively or positively affect youth. Adolescents are a population of interest, given that they use SM frequently, and at times even “addictively,” as some researchers have suggested (Griffiths, 2000, 2005). Several studies have linked SMU to adolescent psychopathology, including internalizing (Keles et al., 2020) and externalizing symptoms (Vannucci et al., 2020). However, gaps in the literature exist. First, methodological weaknesses are prevalent: umbrella reviews have found that most studies of adolescent SMU and well-being are of “low quality” (Orben, 2020, p. 408; Valkenburg et al., 2022). Additionally, researchers typically use cross-sectional designs, making it difficult to determine causality, directionality, and temporal stability or change within these relationships. Furthermore, studies have mainly focused on relationships between SM frequency and depressive symptoms in middle and older adolescents; less research has investigated addictive patterns of usage, anxiety symptoms, externalizing pathology, and younger adolescents. Additionally, limited research has investigated other factors that may relate to SMU, for instance conflictual relationships.

To address gaps in the literature and build upon an ever-growing field of SM research, this study used a nationally representative sample (Heeringa & Berglund, 2020) of American early adolescents and their parents, who participated in four years of data collection starting in September of 2016 as part of the Adolescent Brain Cognitive Development (ABCD) study. Prevalence and characteristics of SMU were explored. Additionally, longitudinal relationships between SMU (frequency and addictive use), relationship functioning (family conflict and prosocial behavior), and psychopathology (internalizing and externalizing symptoms) were investigated using cross-lagged panel models (CLPMs) and random intercept cross-lagged panel models (RI-CLPMs).

Social Media Use

Definition and History

Internet-based platforms created for the purpose of socialization have existed for many years; Kaplan and Haenlein (2010) provided a helpful review of the history of these technologies. *Social networking sites* was the term used to describe websites like Facebook and MySpace, which were developed in the early 2000s. These sites allowed individuals to engage with each other using personalized profiles and instant messages. SM is a relatively newer concept that encompasses social networking sites and generally describes applications used not only to connect with others, but also to create content in a collaborative manner. The creation of content, which occurs in either a public or semi-public context, distinguishes SM from other forms of internet-based communication, like email and texting (Kaplan & Haenlein, 2010). SM is particularly attractive for young people born in the past few decades, who have been called "digital natives" because they have grown up with the internet, so they have unparalleled familiarity with and skilled use of internet-based applications (Kaplan & Haenlein, 2010; Prensky, 2001).

Prevalence and Characteristics

SMU is a ubiquitous part of adolescents' daily lives that may affect interpersonal and psychological functioning. A national survey from 2018 indicated that 95% of adolescents aged 13 to 17 have smartphone access and nearly half go online "almost constantly" (Pew Research Center, 2018). A higher percentage of girls and Hispanics reported being online "almost constantly" compared to boys and Whites, respectively (Pew Research Center, 2018). Regarding SMU specifically, high frequency of SMU (typically defined as time spent or hours per day) among adolescents is prevalent and has increased over generations. Using national data from the Monitoring the Future study (Miech et al., 2017), Kreski and colleagues (2021) found that from 2009 to 2017, prevalence of daily SMU in 8^{th} and 10^{th} grade students increased from 61% to 89% in girls, and from 46% to 75% in boys. Regarding hours per day, 2018 Monitoring the Future data indicated that adolescents reported using SM for about three hours per day on average, with some using almost six hours (Kaur et al., 2020).

Per data collected in 2015, 2016, and 2018, Instagram, Snapchat (Weinstein, 2018), and YouTube (Pew Research Center, 2018) were the most popularly used SM sites among adolescents. Girls and White adolescents used Snapchat most often, boys used YouTube most often, and Black teenagers used Facebook most often (Pew Research Center, 2018). Although these are recent studies, it is important to note that SM technology changes at a rapid pace (van den Eijnden et al., 2016), and SMU research can quickly become outdated. Finally, SM research is typically conducted using mostly White, well-educated samples (Miech et al., 2017). Notably, these limitations are relevant to much of the literature presented throughout this paper.

While much is known about frequency of SMU in adolescents, there is limited research on adolescents' specific SM behaviors or motivations for them. Thus, Swirsky et al. (2021) investigated SM behaviors and found that "lurking," or looking at others' SM profiles and updates, was the most prevalent behavior (p. 1). This has also been called "passive use" (Thorisdottir et al., 2019). However, results of Swirsky et al.'s (2001) study were limited because only behaviors that were predetermined were measured; in other words, open-ended answers were not allowed. Additionally, reported frequency of most of the behaviors was low (Swirsky et al., 2021), suggesting a floor effect. To investigate SMU motives, Throuvala et al. (2019) conducted a qualitative study so that they were not as constrained by measurement limitations. Using data from focus groups, the researchers completed thematic analysis and found that motives for SMU included social comparison, maintenance of relationships, and emotion regulation (ER; Throuvala et al., 2019). Several of the themes were related to control (need for and loss of control) and addictive patterns of use (e.g., "I need to check or I feel bad," Throuvala et al., 2019, p. 169). Indeed, the concept of SM being potentially addictive has become a popular, albeit controversial, topic of study in the SM literature.

SM Addiction

Background. The text revision of the fifth edition of the *Diagnostic and Statistical Manual of Mental Disorders* (DSM-5-TR; American Psychiatric Association [APA], 2022) has categorized addictive disorders in a new way, splitting them up into two sections: substance-related disorders and non-substance-related disorders. The non-substance-related disorders section only contains gambling disorder; however, internet gaming disorder was included as part of the disorders for future study. Non-substance-related disorders are sometimes called "behavioral addictions," or repetitive behaviors that cause functional impairment that is not induced by substances (APA, 2013). The concept of behavioral addiction was first introduced by Peele and Brodsky (1975). Peele (1977) argued that the experience of addiction is more complex than physiological dependence alone, such that it is characterized not only by biological processes but also social and psychological ones. Peele postulated that the symptoms of addiction (e.g., tolerance and withdrawal) that had been historically defined via biological processes could also be explained psychologically. For instance, tolerance could be identified by a person needing to engage in a behavior over and over again, and withdrawal could be defined as the “traumatic disorientation” an individual experiences when they do not engage in the addictive behavior (Peele, 1977, p. 119). Given these circumstances, Peele hypothesized that any activity that provides a person with distraction from pain could develop into an addiction. Importantly, he also pointed out that cultural and individual differences could affect the development of addiction (e.g., if a drug is more accepted rather than stigmatized in a society, it is less likely to be associated with addiction; if a person has a more anxious temperament, they may be more susceptible to addiction). The addiction then further exacerbates people’s ability to cope in adaptive ways (Peele, 1977). Indeed, distraction from pain is not the only possible driver of addictive behavior. For instance, recent research on SM addiction has found that individuals may be more prone to addictive behavior when they are trying to get socialization needs met (Ahmed & Vaghefi, 2021). In their book *Love and Addiction*, Peele and Brodsky (1975) famously illustrated the concept of behavioral addiction with the example of addictive love.

It is important to note that while there has been growing research interest in the construct of behavioral addiction, it remains controversial, and there is not enough evidence to support most behavioral addictions as mental disorders at this time (APA, 2013). Critics (Kardefelt-Winther et al., 2017) have argued that behavioral addiction as it is currently conceptualized is too broad and could lead to pathologizing everyday behaviors (e.g., eating, shopping). Karim and Chaudhri (2012) pointed out that over-pathologizing normal behavior and classifying too many behaviors as “disorders” could damage the public’s belief in diagnostic systems. Another criticism of behavioral addiction is that it is difficult to behaviorally operationalize symptoms like tolerance and withdrawal and to determine parameters for functional impairment. Thus, Kardefelt-Winther and colleagues (2017) recommended that more research should utilize personcentered approaches and investigate whether there is significant functional impairment and persistence associated with behavioral addiction.

Definition. Addictive behavior on internet-based applications is conceptualized similarly to other behavioral addictions. The construct of SM addiction is based on Griffiths's (2005) biopsychosocial framework that identifies addictions, both chemical and behavioral, using six components (Brown, 1993). They are "salience, mood modification, tolerance, withdrawal, conflict and relapse" (Griffiths, 2005, p. 191). In 2014, Griffiths and colleagues explained these characteristics as they relate to SM addiction. First, salience refers to the importance of SM in one's life and the amount of time spent thinking about it. Mood modification describes the emotions one feels as a result of SMU that may be desired as part of a coping strategy. Next, tolerance is characterized by needing to engage in SM more frequently in order to achieve mood modification. Withdrawal symptoms occur when an individual experiences negative emotions and/or physiological changes when they are unable to use SM. Fifth, conflict refers to both interpersonal and intrapersonal impairment within the context of social, occupational, and/or recreational activities resulting from excessive SMU. Finally, relapse describes the process of repeating problematic patterns of usage even after returning to normative use (Griffiths et al., 2014). In sum, SM addiction essentially entails "being overly concerned about SM, driven by an uncontrollable motivation to log on to or use SM, and devoting so much time and effort to SM that it impairs other important life areas" (Andreassen & Pallesen, 2014, p. 4054). Notably, characteristics of SM addiction are similar to those of other addictions, including substance use problems and other behavioral addictions (e.g., overeating, sex; Griffiths, 2005; van den Eijnden et al., 2016). Importantly, SM addiction is a construct that is considered distinct from high-frequency SMU. The most clinically relevant difference is that SM addiction is associated with greater functional impairment than high-frequency use alone. Impairment associated with addictive SMU will be further discussed in a separate section below. It is also notable that different terms including addiction, dependence, disorder, and problematic use have been used to describe impairments associated with excessive SMU. Although researchers use different terms, they all appear to refer to a similar construct (Bányai et al., 2017). For the sake of consistency within this project, the terms SM addiction or addictive SMU will be used. However, it is important to note that SM addiction is *not* a DSM-5-TR disorder. Nonetheless, the terminology of SM addiction has been used by researchers in the field (Andreassen et al., 2017; Griffiths et al., 2014).

Measurement. Originally, measures of social networking addiction focused on Facebook because it was the most popularly used site about a decade ago (see Andreassen & Pallesen, 2014 for review). A commonly used measure was the Bergen Facebook Addiction Scale, which assesses the six characteristics outlined by Griffiths (2005). As SM sites other than Facebook became more prevalent, the Bergen Facebook Addiction Scale was modified to be used for SMU more generally as the Bergen Social Media Addiction Scale (BSMAS; Andreassen et al., 2017). This is the measure that was used for the current project. Another commonly used measure is the Social Media Disorder Scale (SMDS; van den Eijnden et al., 2016), which assesses nine characteristics over the past year. These align with criteria for Internet Gaming Disorder (APA, 2013). Components assessed by the SMDS overlap with those in the BSMAS (Andreassen et al., 2017) and include “preoccupation, tolerance, withdrawal, displacement, escape, problems, deception, displacement, and conflict” (van den Eijnden et al., 2016, p. 480). It is important to note that early research related to online behavioral addictions focused on internet and social networking site use, since those were popular at the time. However, the mechanisms through which those addictions operate are likely different than those relevant to SM addiction, so research cannot be directly compared. Of course, psychometric properties of assessment measures have been validated using SM specifically.

Watson and colleagues (2020) investigated the psychometric properties of three commonly used SM addiction measures (BSMAS, SMDS, and the Social Media Addiction Scale [Al-Menayes, 2015]) and found that all measures were valid and reliable. However, there were differences between measures. For instance, the BSMAS may be more sensitive to gender effects (Watson et al., 2020), which might be valuable when assessing adolescents due to developmental changes that differ by gender. Additionally, the BSMAS displays good convergent and discriminant validity; it is significantly positively correlated with the Addictive Tendencies Scale (Andreassen et al., 2012; Wilson et al., 2010), which is to be expected. The Addictive Tendencies Scale measures salience, control, and withdrawal related to Facebook use (Wilson et al., 2010). Convergent and discriminant validity lend support to the notion that SM addiction is a distinct construct from high SM frequency. Indeed, this distinction was recently highlighted by Valkenburg and colleagues (2022) in an umbrella review wherein authors drew attention to the finding of van den Eijnden et al. (2016) that frequency of SMU only explains six percent of disordered SMU, as measured by the SMDS.

Prevalence. Prevalence of SM addiction in three Dutch adolescent samples used by van den Eijnden and colleagues (2016) in 2014 to 2015 ranged from about 7% to 12%. Other studies have found both lower and higher rates. Using a sample of German adolescents and the SMDS, Wartberg et al. (2020) observed a prevalence of 2.6%; however, their sample had a narrower age range (i.e., starting at 12 rather than ten) compared to other studies. Austermann and colleagues (2021) developed a parent version of the SMDS and, in 2019, found that prevalence of SM addiction in German adolescents who used SM once or more per week was 18.6%. Difference in prevalence estimates across studies may be due to sample and methodological differences; however, they may also indicate that prevalence of SM addiction has increased over time, given that there was a higher estimate in a 2019 sample (18.63%; Austermann et al., 2021) compared to one from 2014 (7.3%; van den Eijnden et al., 2016). This indicates the need for ongoing, current data collection and dissemination. Regarding demographic differences, some studies have shown that younger adolescents are more at risk than older adolescents (Austermann et al., 2021; Boer et al., 2020). Most studies have shown no significant gender differences in addictive SMU (Austermann et al., 2021; Boer et al., 2020; Wartberg et al., 2020), which is interesting given the gender difference in frequency of internet use (Pew Research Center, 2018).

Impairment. Impairment associated with SM addiction is widespread, similar to other addictions (APA, 2013). In their validation study of the SMDS, van den Eijnden and colleagues (2016) found that disordered or addictive SMU was positively correlated with depression, loneliness, low self-esteem, attention deficit, and impulsivity, as well as another addictive behavior, compulsive internet use. It was also positively associated with frequency of SMU, but correlations were only small to moderate (r = .20 to .35; van den Eijnden et al., 2016). Correlations between SM frequency and addiction have been similar in other studies as well (Turel et al., 2018). The small to moderate size of correlations may be explained by biases in self-reporting of these behaviors (e.g., participants being unaware of their true frequency of use and underreporting). A Hungarian study found that adolescents were at risk for SM addiction when they reported using SM for more than 30 hours per week, and these individuals had low self-esteem and high depressive symptoms (Bányai et al., 2017).

Additionally, in a study of SMU across 29 countries, Boer et al. (2020) found that addictive SMU was associated with all the negative outcomes measured, in all of the countries studied, whereas high-frequency use was only associated with some of the negative outcomes and results were less consistent across countries. Specifically, Boer and colleagues (2020) found that addictive SMU was associated with lower life satisfaction, lower school satisfaction, less family support, less friend support, higher schoolwork-related pressure, and more psychological complaints (i.e., feeling low, irritable, nervous; having trouble sleeping) compared to normative use. Interestingly, for some of these relationships, strength varied by country, such that countries with higher prevalence of SM addiction displayed weaker relationships between addiction and variables assessing well-being (Boer et al., 2020), perhaps because addictive use is more normative in those countries. This highlights the need for research that is specific to a certain context. Importantly, a gap in the SM addiction literature is the paucity of American research. As mentioned, several studies have been conducted in European countries (Boer et al., 2020); however, fewer studies have been completed using nationally representative American adolescent samples. Another limitation in the extant literature is the lack of longitudinal studies. One longitudinal investigation using cross-lagged panel models found that symptoms of SM addiction were related to longer sleep latency and daytime sleepiness, and these relationships remained stable across three time points that were each a few months apart (van der Schuur et al., 2019). SM addiction was a stronger predictor of impairing outcomes than SM frequency, and effects were stronger for girls than boys (van der Schuur et al., 2019). More longitudinal research is needed to investigate these and other types of impairments over time.

Although the extant research is limited, especially in adolescent populations, there are a handful of studies that have investigated relationships between SMU, including addictive use and neural functioning. Using a college sample and functional magnetic resonance imaging (fMRI), Turel and colleagues (2014) found that self-reported Facebook addiction was positively correlated with activation of the amygdala-striatal system, which is associated with impulsivity. Using structural MRI and a college-aged population, another study found that SM addiction was associated with reduced gray matter volume in the amygdalae (He et al., 2017), which play a role in impulsive behaviors in response to environmental cues (Koob & Volkow, 2010). Notably, brain regions that have been investigated in these studies of SM addiction have been implicated in reward processing and other addictive disorders (Koob & Volkow, 2010; Noël et al., 2013).

Other researchers have used a behavioral economic approach by investigating *delay discounting*, or the process by which individuals prefer relatively smaller rewards when they are obtained immediately compared with larger rewards provided at a later time. Turel and colleagues (2018) recruited an adult sample and used structural MRI and a monetary delay discounting task to examine SM addiction in relation to gray matter volumes. Results showed a significant negative relationship between SM addiction and gray matter volumes of the insula (Turel et al., 2018), which are associated with the experience of urges or cravings and are implicated in the maintenance of addictive disorders (Noël et al., 2013). Findings additionally showed that delay discounting mediated this relationship, indicating that impulsivity and lack of foresight may be mechanisms that are relevant to brain functioning in the context of SM addiction. It is important to note that some research has not supported links between neural processes. For instance, using an adult sample, Thomson and colleagues (2021) found that SM addiction was not associated with attentional bias, or the preference towards addictive stimuli compared to other environmental cues. Attention bias is a phenomenon that is present in other addictive disorders, as described within the salience component of Griffiths's (2005) biopsychosocial model of addiction. It is also important to note the limitations present within studies of neural functioning and SM addiction. The studies discussed have used relatively small sample sizes, mainly adult populations, and experimental paradigms that may not generalize to real-world situations. It is particularly important to conduct more brain-focused research in adolescent populations, as adolescence is a period during which there is substantial brain reorganization, including neural pruning of gray matter (Durston et al., 2001).

Similarly to other brain-focused studies, Sherman and colleagues (Sherman et al., 2016, 2018) used fMRI, but investigated a wider age range of adolescents and a specific feature of SM, "likes," using a simulation resembling Instagram. Sherman et al. (2018) found that engaging in SM by liking others' posts and receiving likes on one's own posts activated neural regions associated with reward, like the striatum and ventral tegmental area. Providing likes to others was also associated with activation of the ventromedial prefrontal cortex, a brain region implicated in prosocial behavior (Sherman et al., 2018). In another study, Sherman and colleagues (2016) found that when adolescents viewed photos with more likes compared with those with fewer likes, they displayed higher activity in brain areas involved in reward processing and social cognition. Given that SMU is inextricably linked with social functioning, it is imperative that more research investigate the role that SMU plays in relationships, not only with peers but also with other individuals that are important in adolescents' lives, like parents and other family members.

Theories of SMU

Contextual Framework. Drawing from multiple other theories and fields of study, Nesi and colleagues (2018) developed a helpful framework for considering how SMU affects the lives of adolescents. The *transformation framework* posits that there are seven characteristics of SMU that are not present in face-to-face communication, and these change the way that adolescents interact with others. First, *asynchronicity* refers to when there are delays in features of communication. Additionally, *cue absence* describes the lack of physical indications involved in interactions. An example that has both asynchronicity and cue absence is direct messaging: adolescents who message a peer have time to plan what they are going to say, and they do not see their peer's facial expressions afterwards. These aspects could facilitate communication for adolescents who have social anxiety; however, they could also increase the chance of misunderstandings and cause conflict between friends. *Permanence* and *publicness* are two other characteristics that differ on SM, such that content can potentially be available for a long period of time and communicated to a large audience. Additionally, *availability* is the immediacy and ease with which interactions on SM can occur. These three aspects increase exposure and accessibility to wider communities, which could enhance opportunities for social support, especially for ostracized teens. Alternatively, these aspects could also exacerbate upward social comparisons, given the wider audience. *Visualness* refers to the emphasis on photos and video; this could also lead to upward social comparisons via body image concerns. Finally, *quantifiability* describes the inclusion of social metrics (e.g., "likes," comments, views). Again, this could affect adolescents' concerns about social status. Quantifiability could also lead to increased cyberbullying; for example, aggressive adolescents may be reinforced for their antisocial behavior via "likes" and comments. Importantly, Nesi and colleagues (2018) acknowledged that different SM applications have different levels of these seven characteristics. For example, there is lower publicness but higher visualness associated with private photo messaging apps like Snapchat compared to public forum apps like Reddit. Ultimately, this transformation framework can be applied not only to peer relationships, as specified by the authors, but to other relationships and various types of psychopathology, including SM addiction.

Addiction Theories. Regarding the etiology of SM addiction, there are a few relevant theories that overlap with the transformation framework. They were originally developed to explain internet addiction more broadly, but they have also been applied to SM behavior (Turel & Serenko, 2012). Davis's (2001) cognitive behavioral model posits that individuals' addictive usage is reinforced by certain stimuli (e.g., "likes") and exacerbated by cognitive distortions (e.g., believing one is more socially competent online). Another theory is the socio-cognitive model, which is based on Bandura's (1991) social cognitive theory of self-regulation (LaRose et al., 2003). It hypothesizes that difficulties with self-regulation lead to formation of habits that are often paired with maladaptive cognitions; these problems are characteristic of SM addiction. For instance, an individual who struggles with self-control may find it difficult to limit SM use and thus form a habit of use, then may experience sadness and guilt about this usage. Finally, the social skill model states that individuals who have deficits in the abilities needed to present themselves to others prefer online communication and thus tend to devote more energy and resources into maintaining their social lives online and neglect face-to-face activities, leading to symptoms of addiction (Caplan, 2003). Caplan (2005) found support for this theory using structural equation modeling. Perhaps unsurprisingly, each of these theories share features of cognitive and behavioral deficits that are often characteristic of other psychopathology, including internalizing and externalizing symptoms. In line with a diathesis-stress model, it seems that a similarity across these theories is that addiction stems from a combination of pre-existing risk factors (e.g., low self-esteem and cognitive distortions characteristic of internalizing symptoms; reward seeking characteristic of externalizing symptoms) and social interactions that exacerbate them. Indeed, overall social functioning is crucial to consider when studying SMU, especially in adolescents, who undergo developmental changes related to their relationships.

Social Functioning

Given that SMU fundamentally changes the way that adolescents socialize, it is important to investigate how SMU affects their relationships with others. One way to do this is through the lens of prosocial behavior. Prosocial behavior, or action intended to help other people (Eisenberg & Fabes, 1998), is positively associated with multiple positive outcomes during adolescence, including self-regulation (Padilla-Walker & Fraser, 2014), academic success (Gerbino et al., 2018), and psychological well-being (Littman-Ovadia & Steger, 2010). It is also negatively associated with psychopathology, including internalizing and externalizing symptoms (Flouri & Sarmadi, 2016). Despite these positive associations, limited research has focused on adolescence and the development of prosocial behavior throughout this period. Instead, research has primarily focused on early childhood and adulthood (El Mallah, 2020). Longitudinal research is also limited. Additionally, there is even less research on how SMU relates to prosocial behavior, especially given that much of the SM literature disproportionately focuses on antisocial behavior (e.g., cyberbullying). In fact, Lysenstøen and colleagues (2021) conducted a systematic review of research investigating SMU and online prosocial behavior in adolescents between 2014 and 2021, and only two studies met eligibility criteria (Erreygers et al., 2017, 2019). These studies will be further discussed below.

Prosocial behavior is an important construct to study in adolescents because of the biopsychosocial changes that occur during this time that render social cues more salient (Casey et al., 2008; Steinberg, 2008). According to attachment theory, as adolescents build autonomy, they tend to “de-idealize” their parents (Steinberg, 2005) and incorporate other figures, namely peers, into their attachment hierarchies (Rosenthal & Kobak, 2010). Importantly, attachment relationships with peers are unique from those with parents because adolescents are equal to their peers, which allows for mutual support seeking and caregiving (Allen & Tan, 2016). Although parents remain a part of their support systems, adolescents tend to prefer peers for support in situations that are not emergencies (Zeifman & Hazan, 2008). In fact, research that has measured stress via cortisol levels has found that parents' support during stressful situations is less effective for adolescents compared to younger children (Hostinar et al., 2015). Literature on prosocial behavior also demonstrates distinct findings for adolescents' behavior towards peers versus family members. During adolescence, friends, more so than strangers or parents, are the most common targets of prosocial behavior (Padilla-Walker & Carlo, 2014). Padilla-Walker and colleagues (2018) used latent growth curve analyses to investigate longitudinal trajectories of prosocial behavior during adolescence in a Dutch sample. Results showed that prosocial behavior towards peers increased steadily across adolescence, whereas prosocial behavior towards strangers increased then flattened out, and prosocial behavior towards family members remained stable then increased towards the end of adolescence (Padilla-Walker et al., 2018).

Studies have also demonstrated differences in relationships between prosocial behavior and symptoms of psychopathology. In a longitudinal study, Padilla-Walker and Christensen (2011) found that positive parenting, empathy, and self-regulation were predictors of prosocial behavior towards both strangers and friends. However, in analyses investigating prosocial behavior towards family members, only positive parenting (specifically mothering) was a predictor. Another longitudinal study utilizing cross-lagged panel models indicated that prosocial behavior towards friends directly predicted more delinquency two years later (Padilla-Walker et al., 2015). This aligns with other research on externalizing behavior in adolescents that indicates that in the presence of peers, teenagers are more likely to engage in risky behaviors (Steinberg, 2008). Additionally, the study found a bidirectional relationship between prosociality towards peers and anxiety, such that more anxiety predicted more prosocial behavior two years later and vice versa. The relationship between prosocial behavior and anxiety was mediated by strength of connections with friends. On one hand, this result may reflect peers' tendency towards support seeking when they are feeling negative emotions, but it also may suggest that support seeking may exacerbate those emotions (e.g., co-rumination). Conversely to the findings for peer prosociality, prosocial behavior towards family members indirectly predicted less internalizing and externalizing problems; parental support acted as a mediator (Padilla-Walker et al., 2015). Another study demonstrated a more complex picture of relationships between emotions and prosocial behavior that occurs online specifically. Erreygers and colleagues (2017) studied Dutch adolescents and found that the experience of both negative and positive emotions was related to more online prosocial behavior. Errasti and colleagues (2017) found a similar result, that the expression of both positive and negative emotions on social networking sites was related to higher empathy. These studies did not differentiate between prosocial behavior towards peers or other individuals; however, the measures seemed more focused on peer interactions.

Notably, there are individual and gender differences in prosocial behavior. As reviewed by Padilla-Walker and colleagues (2018), dispositional theories of prosocial behavior posit that the behavior varies as a function of one's personality and self-perception, for instance, whether they are altruistic or have a strong sense of morality. Relational theories, on the other hand, propose that prosocial behavior may also vary as a function of whom the behavior is directed towards. Research has suggested that dispositional traits are more relevant to prosocial behavior with strangers and peers, whereas relationship qualities appear to be more important for prosocial behavior with family members. Given that these constructs may be very specific to individuals, it is important to study them in a way that can investigate changes at the individual level, and while taking demographic differences, like gender, into account. Van der Graaff and colleagues (2018) conducted a 6-year longitudinal study that investigated changes in prosocial behavior across adolescence in a Dutch sample. They found that for boys, prosocial behavior was stable until middle adolescence, increased, then decreased. For girls, prosocial behavior increased until late adolescence and then decreased. Using cross-lagged panel modeling, the study also found that for both genders, empathy predicted more prosocial behavior in later years. Prosocial behavior also predicted more empathy later, but only for girls (Van der Graaff et al., 2018). Another Dutch study that investigated within-person effects using multilevel modeling found that happiness earlier in the day predicted online prosocial behavior later in the day, but only in adolescent girls and not in boys (Erreygers et al., 2019).

Given the changes in relationships with parents and peers during adolescence, it is important to study both, and how SMU may impact them or vice versa. It is perhaps even more important to study these variables in the context of the COVID-19 pandemic, which has further altered how adolescents interact with each other. Indeed, in a recent systematic review of international studies examining protective factors of adolescent mental health in the context of social isolation due to the pandemic, prosocial behavior was found to be one of the strongest protective factors, along with social connectedness and self-esteem (Preston & Rew, 2022).

Links to SMU

Prosocial Behavior. Peers are the most frequent targets of prosocial behavior during adolescence (Padilla-Walker & Carlo, 2014). Although Nesi and colleagues' (2018) transformation framework hypothesized that SM *changes* peer relationships, studies have indicated that adolescents engage in at least some similar activities online as they do in person. In a review of dozens of studies, Yau and Reich (2018, p. 339) investigated whether traditional components of friendships (i.e., “self-disclosure, validation, companionship, instrumental support, conflict, and conflict resolution [Parker & Asher, 1993]”) exist in the context of online communication. Results indicated that these qualities were evident online, across both image-based and text-based platforms (Yau & Reich, 2018). These findings align with co-construction theory of internet use, which states that adolescents create similar developmental issues online as they do in person (Subrahmanyam et al., 2006). However, this model also agrees with the transformation framework in that it acknowledges that there are some differences online compared to in-person contexts (e.g., increased anonymity; Subrahmanyam et al., 2006). Ultimately, it seems that there are both positive and negative aspects of peer interactions that evidence themselves in both traditional and SM contexts.

A few other theories are relevant to the discussion of SMU specifically as it affects peer relationships. Notably, they originated in internet use literature and may not capture all the nuances associated with newer technologies. These include the “poor get rich,” “rich get richer” (Kraut et al., 2002), and “poor get poorer” (Ophir et al., 2016) models, and they share similarities with Caplan’s (2005) social skill model of internet addiction. Kraut and colleagues (2002) proposed the “poor get rich” model, which hypothesizes that more socially disadvantaged individuals will use the internet as a less traditional form of socialization, and they will benefit from this use. Somewhat similarly, the “rich get richer” model posits that people who have more social skills will also benefit from online social interaction (Kraut et al., 2002). Years later, Ophir and colleagues (2016) proposed a different model, “poor get poorer,” which states that individuals, namely adolescents, who have less social support may also have difficulties with online social interaction.

Parallel to theory, the empirical literature suggests patterns that are neither completely positive nor negative. One distinct pattern, however, is that research findings linking SMU and peer functioning appear to be more positive compared to family functioning research. Vannucci and Ohannessian (2019) found that for some adolescents, SMU predicted high close friendship competence and perceived friend support. Interestingly, this result only applied to individuals who used Instagram and Snapchat most frequently. Research has also shown that more use of social networking sites is related to higher offline social competence (Tsitsika et al., 2014). One longitudinal study found that initiation of online friendships predicted initiation of offline friendships one year later (Metzler & Scheithauer, 2017). Other studies, both cross-sectional (Errasti et al., 2017) and longitudinal (Vossen & Valkenburg, 2016), have found that higher frequency SMU is related to higher empathy in adolescents. These findings may align with either "poor get rich" or "rich get richer" models; however, it is unclear because they did not investigate the effects of baseline social competence. One study that may more specifically align with "rich get richer" and "poor get poorer" models was conducted by Khan and colleagues (2016). Results indicated that adolescents who spent more time socializing both online and offline had the highest self-concepts, or positive perceptions of themselves; however, those who socialized frequently online but not offline had the lowest self-concepts (Khan et al., 2016). Unfortunately, this study was cross-sectional, so conclusions about whether they support theoretical models cannot necessarily be drawn.

Compared to research on SMU frequency, there have been fewer studies on addictive SMU. One study found that it is negatively related to empathic concern and perspective-taking in adolescents (Dalvi-Esfahani et al., 2021). Another limitation of extant research is that like the parent literature, only one of the discussed studies was conducted in an American sample (Vannucci & Ohannessian, 2019); the others investigated European adolescents.

Family Conflict. Compared with research on peer relationships, there is less research on how SMU affects parent-child and broader family relationships; however, extant studies generally indicate that higher frequency and more addictive use are associated with more negative relationships. Sampasa-Kanyinga and colleagues (2020) studied Canadian adolescents and early adults aged 11 to 20 years old and found that self-reported frequency of SMU more than 2 hours per day was related to more negative parent-adolescent relationships. Notably, the finding was only significant for relationships between mothers and daughters, fathers and daughters, and fathers and sons, but *not* mothers and sons. Relationship quality was measured by asking how well adolescents were "getting along" with their parents (Sampasa-Kanyinga et al., 2020, p. 795). Using a more standardized measure of family functioning (i.e., the Family APGAR; Smilkstein, 1978), German researchers (Wartberg et al., 2020) found that lower family functioning in four different domains was related to problematic social media use in adolescents. Sela et al. (2020) found similar results in Israeli adolescents: negative family environments as measured by the Family Environment Scale (Moos & Moos, 1994), which assesses cohesion, expressiveness, and conflict in interpersonal relationships, were related to high frequency and addictive internet use. However, this study only investigated internet use, not SMU specifically (Sela et al., 2020). Unfortunately, all these studies were cross-sectional; therefore, it is difficult to determine causation and direction of relationships. One longitudinal study by Vannucci and Ohannessian (2019) collected data on American adolescents two times, six months apart. Results indicated that higher frequency of SMU predicted frequent family conflict and low perceived family support over time (Vannucci & Ohannessian, 2019). However, this was a relatively brief longitudinal study; more research is needed that spans years rather than months.

Psychopathology in Adolescents

Internalizing Symptoms

Prevalence and Characteristics. Internalizing disorders are common in adolescence. Data from the National Comorbidity Survey–Adolescent Supplement (NCS-A; Merikangas et al., 2010) indicate that about 14% of teenagers have a lifetime prevalence of any mood disorder, and 32% have a lifetime prevalence of any anxiety disorder. Major depressive disorder (MDD) is the most common depressive disorder, and specific phobia and social phobia are the most common anxiety disorders (Merikangas et al., 2010). Females are at higher risk for developing internalizing disorders. Compared to White adolescents, non-Hispanic Black adolescents reportedly experience increased rates of anxiety disorders, and Hispanic adolescents experience higher rates of mood disorders. Prevalence of anxiety disorders remains relatively stable across adolescence, whereas prevalence of depressive disorders increases over time. Given this increase, it is crucial to study depressive symptoms in adolescence longitudinally.

Links to SMU. In line with social comparison theory (Festinger, 1954), internalizing symptoms may be related to SMU because of online social comparisons, which could lead to lower self-esteem and body image issues and in turn, more depression and anxiety (Kelly et al., 2018). The relationship could also go in the other direction, such that more depressed adolescents use SMU more frequently and addictively as part of attempts to withdraw from more traditional social activities or as part of ER strategies. A recent systematic review of studies investigating associations between SMU and internalizing disorders in adolescents found 13 relevant studies that were published within the past 10 years (Keles et al., 2020). The pattern of results supported positive relationships between internalizing symptoms and SMU. However, extant literature is hindered by methodological weaknesses that limit the ability to draw conclusions about directions of effects. Keles and colleagues (2020) found that the quality of studies included in their review was generally only poor to fair. Furthermore, most studies have been cross-sectional and conducted in European samples of middle and older adolescents, limiting generalizability to other populations. Finally, while much research has investigated depression and SM frequency, there are fewer studies on internalizing symptoms more broadly and SM addiction (Keles et al., 2020).

Some recently published studies have used longitudinal data and strong analytical techniques that separate between-person from within-person effects (e.g., random intercept cross-lagged panel models [RI-CLPM; Hamaker et al., 2015]). In contrast with findings from cross-sectional research, results of these longer-term studies have generally not supported longitudinal within-person relationships between SM frequency and depression (Coyne et al., 2020; Houghton et al., 2018; Schemer et al., 2021). One study using a sample of Finnish adolescents and RI-CLPM found that increases in depressive symptoms significantly predicted increases in social networking frequency over time; however, the relationship was weak, and the researchers only investigated “active” use (e.g., posting pictures; chatting), not overall usage. The reverse relationship was not significant (Puukko et al., 2020). Vuorre et al. (2021) investigated changes in relationships between SM and mental health outcomes across three nationally representative samples over the last ten years. They found that SM use has become more strongly associated with emotional problems in general, but less strongly associated with depression specifically. However, the magnitudes of the effects were small (Vuorre et al., 2021).

Boer and colleagues (2021) used RI-CLPM and investigated both SMU frequency and addictive use in a Dutch sample of adolescents. Results showed that while there was no within-person cross-lagged relationship between SMU frequency and depressive symptoms; there was a relationship between SMU addiction and depressive symptoms. Specifically, adolescents who reportedly experienced increases in addictive SMU also experienced increases in depressive symptoms one year later. Notably, the reverse paths (i.e., depression predicting SMU addiction) were not significant. Boer and colleagues (2021) also investigated mediators, which is a strength compared to other studies. Surprisingly, they found that upward social comparisons, cybervictimization, school achievements, or in-person contact with friends did not mediate the relationship between SMU addiction and depression (Boer et al., 2021). Lastly, Marciano and colleagues (2022) assessed Swiss early adolescents over three years using RI-CLPM analyses and found that duration of internet use, including SMU, predicted depression levels at later time points, and vice versa. However, the reverse path was smaller in magnitude. Thus, there are mixed results regarding the within-person relationship between SM frequency and internalizing symptoms, and more consistent results for the association between SM addiction and internalizing symptoms.

Externalizing Symptoms

Prevalence and Characteristics. Externalizing disorders are also common in adolescence; lifetime prevalence of any behavior disorder is almost 20%, and lifetime prevalence of any substance use disorder is about 11% (Merikangas et al., 2010). However, substance use is relatively lower in younger adolescents (Lisdahl et al., 2021), and it is subsumed in a somewhat separate literature than externalizing symptomology, so this study will only focus on behavior disorders. Other externalizing disorders include oppositional defiant disorder (ODD), which is the most common behavior disorder in adolescents, and conduct disorder (CD). Prevalence of behavior disorders remains relatively stable over time and appears to be similar across racial groups. In contrast to higher female risk for internalizing disorders, there is higher male risk for externalizing disorders (Merikangas et al., 2010).

Links to SMU. Compared to research on internalizing disorders and SMU, there is far less research on externalizing disorders and SMU. In line with social learning theory (Bandura, 1971) and more broadly with developmental mismatch models of adolescent brain development (Casey et al., 2008; Steinberg, 2008), SMU may be related to externalizing symptoms because adolescents who see their friends posting content about risky behaviors in a positive light may be influenced to engage in similar behaviors (Vannucci & Ohannessian, 2019). Relatedly, an fMRI study by Sherman and colleagues (2016) found that when adolescents viewed risky photos while using an Instagram-like simulation, neural activation in their cognitive control network decreased, compared to when they viewed neutral photos. The relationship may also go in the other direction. Given that adolescents with externalizing disorders have high reward sensitivity (Carlson et al., 2013), they may be more prone to use SM more to obtain "likes," which have been shown to activate reward processing areas of the brain (Sherman et al., 2018). It could also be possible that individuals with externalizing symptoms who are prone to antisocial behaviors may engage in higher frequency SMU in activities like cyberbullying (Fisher et al., 2016).

Using a longitudinal cohort design and a nationally representative sample of American adolescents, Riehm and colleagues (2019) found that more frequent SMU was associated with increased risk of comorbid externalizing and internalizing problems, but not externalizing problems alone. Another longitudinal study of American adolescents found that more SMU predicted more delinquent behaviors (Vannucci & Ohannessian, 2019). Results from a study using the same dataset also found a positive cross-sectional relationship between more SMU and poorer behavioral conduct (Ohannessian & Vannucci, 2021). Finally, a Norwegian study found similar results over six months: higher frequency of SMU predicted more conduct problems in adolescents (Brunborg & Andreas, 2019). Unfortunately, none of these studies used statistical analyses that identify within-person changes. Additionally, they are limited by many of the same methodological weaknesses (e.g., focus on frequency of use not addictive use) as the studies of SMU and internalizing symptoms.

COVID-19 Pandemic

One environmental change that significantly affected both the general population and adolescents specifically was the COVID-19 pandemic and associated lockdowns. Given that a portion of data used in this study was collected during the pandemic, it is important to consider its potential effects on variables of interest. Some research has begun to investigate related topics. Cauberghe and colleagues (2021) collected data in April of 2020 to investigate whether SM played a role in helping adolescents cope with psychological distress in the context of the pandemic. Results showed that higher levels of anxiety were related to higher levels of active and social coping, whereas more loneliness was only related to social coping. Additionally, mediation analyses showed that active coping positively mediated the relationship between anxiety and happiness, such that anxious adolescents who reported more active coping in turn reported more happiness. On the other hand, adolescents who reported higher levels of loneliness reported using SM for social coping more often; however, this type of coping style was not related to more happiness (Cauberghe et al., 2021). Limitations of this study include that it was cross-sectional and utilized relatively brief measures of symptoms. The findings highlight that there may be both positive and negative effects of SMU on mental health, supporting the need for more studies that can investigate causation and within-person differences. Marengo and colleagues (2022) also collected data during the pandemic. During the 2020 to 2021 school year, they surveyed Italian adolescents. Using the BSMAS, they found that teenagers who used Instagram and TikTok reported the highest levels of SM addiction, compared to other apps, like Facebook and Twitter. Adolescents who only used WhatsApp and YouTube reported the lowest levels of SM addiction. Results also showed that TikTok use predicted SM addiction more strongly than time spent on other apps, perhaps because its content is highly visual and more stimulating than other apps. This may indicate that there may be more negative effects of SMU depending on the type of platform an individual uses, which also highlights the need for within-person analyses.

A limitation of research conducted during the pandemic is that it is difficult to parse apart the impact of the environmental changes associated with the lockdown from individual differences in distress levels that may have existed prior to the pandemic. To address this, Muzi and colleagues (2021) recruited an adolescent sample during the pandemic and compared their data to data collected before the pandemic from a group that was similar in terms of demographics. Data were collected from Italian adolescents aged 12 to 17 in March through May of 2020 and compared to data collected from adolescents living in the same region between 2019 and January 2020. Both were community samples. Using the youth Child Behavior Checklist self-report and SMDS, analyses showed that the pandemic group reported more externalizing problems and more problematic SMU, but fewer internalizing symptoms. Additionally, the authors found that higher levels of problematic SMU predicted more emotional and behavioral problems (Muzi et al., 2021). This study indicated that the COVID-19 pandemic may have exacerbated problematic SMU and mental health problems. Limitations include that like other similar studies, it was cross-sectional. Additionally, most participants were female, limiting generalizability. Lastly, similarly to other studies on SMU, data were collected in Europe, so generalizability to American adolescents is limited. It is important for these relationships to be further investigated in an American sample with a design that can better investigate bidirectional, within-person relationships between variables.

Previous ABCD Findings

There have been a few studies using ABCD data (the dataset being used in the current study) that have investigated cross-sectional relationships between SMU and related constructs and psychopathology as measured by the Child Behavior Checklist at baseline. Paulus and colleagues (2019) investigated overall screen media frequency (e.g., SM, TV, video games) and found that it was related to brain differences associated with externalizing symptoms, but not those associated with internalizing symptoms. However, the researchers did not examine SMU separately from the other types of screen media (Paulus et al., 2019). Guerrero et al. (2019) did investigate SM specifically, and found similar results: frequency was not related to internalizing symptoms or social problems, but it was related to externalizing symptoms, specifically rule-breaking and aggressive behaviors. Since these studies used cross-sectional baseline ABCD data, they represent a starting point for additional ABCD research. Overall, these studies, along with prior studies, seem to suggest that there may be a stronger relationship between externalizing symptoms and SMU (at least frequency) compared to internalizing symptoms and SMU. However, they were limited because they did not address addictive SMU or relationship functioning. Additionally, due to their cross-sectional nature, they were unable to parse apart between- and within-person effects. The current study will build upon these studies by investigating relationships between SMU, including addiction, psychopathology, and relationship functioning longitudinally using multiple measures and reporters.

Current Study

Extant literature is limited by several methodological weaknesses and does not present a consistent picture of adolescent SMU and how it relates to psychopathology. Most studies have used cross-sectional, mono-method designs, and they have mainly studied frequency of SMU, neglecting to investigate other features including problematic, or "addictive" use. Additionally, samples are typically composed of older adolescents in European countries; more research is needed in younger, American adolescents. Findings are mixed in that some studies show positive relationships between SMU and psychopathology, whereas others do not. Furthermore, while much research has investigated SMU in relation to depressive symptoms, studies on symptoms of broader internalizing (including anxiety) and externalizing behaviors are lacking. Additionally, few longitudinal studies examine the interplay between SMU and social functioning. Lastly, updated, long-term research is constantly needed to improve understanding of SMU in adolescents, a phenomenon that is ever-changing and might display differences over time. Therefore, the current study proposed to investigate relationships between SMU (frequency and addiction), social functioning (prosocial behavior and family conflict), and psychopathology (internalizing and externalizing symptoms) in young adolescents. Strong statistical techniques, cross-lag panel modelling and random intercept cross-lagged panel modelling, were used to investigate hypotheses so that both between-person and for some models, within-person effects could be examined. Directions of effects were also clarified.

Hypotheses

Given that previous research shows there is more impairment associated with SM addiction than SM frequency (Boer et al., 2020), different hypotheses were proposed for these variables. As described above, existing literature generally supports relationships between SMU and more negative outcomes (e.g., family conflict, externalizing symptoms, and internalizing symptoms). The exception to this is prosocial behavior, as there is some evidence that SMU increases empathy and closeness with friends. Additionally, although many cross-sectional studies have shown relationships between SMU and internalizing symptoms, research that has utilized within-person, longitudinal designs like the current study have not found relationships between these symptoms and SM frequency, but they have supported relationships between internalizing symptoms and SM addiction. Thus, the following hypotheses were proposed regarding SM frequency:

1. There would be bidirectional relationships between higher levels of SM frequency and higher levels of family conflict and externalizing symptoms.
2. There would be a bidirectional relationship between higher SM frequency and more prosocial behavior.
3. There would *not* be a significant relationship between SM frequency and internalizing symptoms.

Furthermore, the following hypotheses were proposed regarding SM addiction:

1. There would be bidirectional relationships between higher levels of SM addiction and higher levels of family conflict, externalizing symptoms, and internalizing symptoms.
2. There would be a bidirectional relationship between higher SM addiction and less prosocial behavior.

3. Compared to the effects for SM frequency, the effects for SM addiction would be stronger in magnitude.

Gender and Developmental Differences:

1. Gender differences were investigated by testing for equality constraints across gender groups.
2. Developmental differences were explored by testing for equality constraints across time points.

Chapter 2: Methods

Procedure

The ABCD study was developed to investigate psychological and neurobiological changes in development from pre-adolescence through young adulthood. Data collection at 21 sites throughout the country is ongoing, and the study will ultimately include 10 years of follow-up visits (Garavan et al., 2018). All participants provided informed consent. To obtain access to ABCD data for the purposes of this project, a Data Use Certification form was completed and submitted to the National Institutes of Health Data Access Committee. Access was granted on August 30, 2021, and renewal access for each additional year of the project was granted. Access approval letters are displayed in Appendices A and B.

The ABCD baseline cohort consisted of 11,878 participants ages 9 to 10 years old, a portion of whom were twins. Participants were recruited from American schools using multi-stage probability sampling that aimed to align sociodemographics with those from census data so that the sample would be nationally representative. However, it is important to note that the final sample does not necessarily reflect national sociodemographics, as there were some sources of selection bias (e.g., participants were required to live within 50 miles of a major medical or research facility due to brain imaging requirements of the study; Heeringa & Berglund, 2020). Data Release 4.0 is currently available and includes data from the full cohort for the baseline, 1-year, and 2-year follow-up time points. It also includes data from about half the cohort for the three-year follow-up time point. For the purposes of this study, the baseline time point will be referred to as Year 1, and the follow-up time points as Years 2, 3, and 4. Data for Year 1 were collected from 2016 to 2018, Year 2 from 2018 to 2020, Year 3 from 2018 to 2021, and Year 4 from 2019 to 2021 (for the current dataset). Year 2 data collection was completed by February of

2020. When the COVID-19 pandemic restrictions began in March of 2020, during Year 3 data collection, more remote data collection methods (i.e., participants answering questionnaires at home on personal laptops rather than in-person during lab visits) were utilized.

Measures

Information about measures used in the ABCD study was obtained from Barch and colleagues (2018), as well as ABCD materials. Demographics and SMU characteristics were explored in preliminary analyses. Data about validity and reliability of measures are from previous studies not associated with ABCD. All relevant items of measures are displayed in Appendices E through H.

Demographics

Parents completed the ABCD Demographics Survey, which includes items from the PhenX toolkit (Stover et al., 2010) about adolescent age, birth sex, and race, as well as parent education and income. For the purposes of this study, in line with previous ABCD studies, the binary sex variable was used for gender. The gender identity variable was explored, and for nearly all participants, birth sex aligned with gender identity.

Screen Time Survey

General Characteristics. Adolescents completed the ABCD Screen Time Survey at all time points. Selected items were used for the purposes of this study. Adolescents were asked about frequency of use at all time points and addictive behaviors at Years 3 and 4. At Years 3 and 4, they were also asked about general characteristics of usage. One item asked which SM account they used the most, with answer choices including Facebook, Instagram, Snapchat, Twitter, YouTube, Pinterest, Tumblr, Reddit, Multiplayer Videogame Online Chatting, TikTok, and Other. There were also items assessing the number of people or groups that adolescents were following and the number of followers they had. Also included were items about privacy (i.e., whether each account was public or private and whether they had any SM accounts they kept secret from their parents).

Frequency. To assess SM frequency (SMF), adolescents were asked how many hours and minutes they typically spent, on weekdays and weekend days. Frequency of use was measured at all time points; however, there were differences in the questions used. At Years 1 and 2, the question assessed time spent on "social networking sites like Facebook, Twitter, Instagram, etc.?" and at Years 3 and 4, the item asked about time spent on "social media apps (e.g., Snapchat, Facebook, Twitter, Instagram, TikTok, etc.?)" Also, for Years 1 and 2, the ceiling for response options was four hours of usage plus minutes. For Years 3 and 4, the ABCD team updated the measure so that the ceiling was 23 hours of usage plus minutes. For the purposes of the current study, weighted averages of the weekday and weekend day frequencies were calculated to determine daily use. Additionally, for consistency, variables were recoded so that for all time points, the ceiling was four hours.

Addiction. Addictive behavior in the ABCD Screen Time Survey was quantified using six items from the Bergen Social Media Addiction Scale (BSMAS; Andreassen et al., 2017). This measure asks about behaviors commonly associated with problematic SM usage (e.g., "I feel the need to use social media apps more and more;" "I use social media apps so much that it has had a bad effect on my schoolwork or job"). In the ABCD study, items were rated on the following Likert scale: 1 = *never;* 2 = *very rarely;* 3 = *rarely;* 4 = *sometimes;* 5 = *often;* 6 = *very often*. However, the original measure utilizes a slightly different Likert scale that does not include a "never" option (1 = *very rarely*, 2 = *rarely*, 3 = *sometimes*, 4 = *often*, 5 = *very often*). To improve interpretation and comparability to other research that also uses the BSMAS, the variable was recoded so that the values go from 0 to 5 instead of 1 to 6. In line with the original measure, sum scores were used to calculate total addiction.

Family Environment Scale–Family Conflict Subscale (FES; Moos & Moos, 1994)

The ABCD study used a modified version of this scale from the PhenX toolkit (Stover et al., 2010). It assesses the amount of conflict that is expressed within the family. Adolescents completed this at all time points. However, due to an ABCD error, data for Year 4 are missing from the 4.0 Data Release and so cannot be used. The measure contains nine items (e.g., "We fight a lot in our family") that are rated as either *true* or *false*. Endorsed responses were summed to create a total score; higher scores indicate more family conflict. Reliability of this subscale has been good in adolescent samples (Cronbach's $\alpha = 0.85$; Sela et al., 2020).

Prosocial Behavior Scale (PBS; Goodman et al., 1998)

Adolescents completed the PBS at all time points. The ABCD study used the three items from the Prosocial Scale of the Strengths and Difficulties Questionnaire (Goodman et al., 1998) with the highest factor loadings. Items (e.g., "I am helpful if someone is hurt, upset, or feeling sick") were rated on a Likert scale (0 = *not true*, 1 = *somewhat true*, 2 = *certainly true*). Mean scores were used. Reliability of this measure in an adolescent sample was good (Cronbach's α = .81; Domoff et al., 2019).

Internalizing Symptoms

Adolescents completed the youth version of the Brief Problem Monitor (BPM; Achenbach et al., 2011), which is a brief, self-report version of the Child Behavior Checklist (Achenbach, 2009). This was administered starting at age 12, or Year 2 and also administered at Years 3 and 4. The Internalizing subscale includes 6 items (e.g., "I am unhappy, sad, or depressed"), rated on a likert scale (*0 = not true*, *1 = somewhat true*, *2 = very true*). In the validation sample, reliability of the Internalizing subscale was good (Cronbach's α = .78; Achenbach et al., 2011). In accordance with Achenbach and Rescorla's (2001) recommendation for use of the CBCL in research, raw scores were used for data analyses.

Externalizing Symptoms

For Years 2 through 4, adolescents also completed the Externalizing subscale of the BPM. This subscale contains seven items (e.g., "I disobey my parents") and response options are the same as the Internalizing subscale. Raw scores were used. In the validation sample, reliability of the Externalizing scale was good (Cronbach's α = .75; Achenbach et al., 2011).

Data Analysis

To test the hypotheses about SM frequency, RI-CLPMs were used. RI-CLPM is a multilevel structural equation modeling approach that was introduced by Hamaker and colleagues (2015) as an alternative to the traditional cross-lagged panel model (CLPM). This type of model is "crossed" because it investigates relationships between variables in both directions. It is "lagged" because it examines these relationships over multiple time points. CLPM is preferred over cross-lagged correlations because it better accounts for stability over time by using autoregressive parameters, which are indications of future values of variables based on their past values. However, the assumption of the CLPM is that everyone changes around the same means, and thus the autoregressive parameters represent temporal stability only and not trait stability. This is problematic because there could be unmeasured traits that cause differences between individuals and bias results (Hamaker et al., 2015; Kearny, 2017).

In contrast, the RI-CLPM accounts not only for temporal stability but also trait stability, and as such, it considers both between-person differences and within-person differences over time. The technique differs from the traditional CLPM because it adds random intercepts to the model to represent individuals' deviations from group means (i.e., stable trait-like characteristics). Additionally, the autoregressive parameters in the RI-CLPM are different from those in the traditional CLPM because they represent within-person carry-over effects. Ultimately, cross-lagged parameters in the RI-CLPM indicate how much individuals change in one variable based on deviations from their expected score on the other variable, while controlling for carry-over effects in each variable (Hamaker et al., 2015). RI-CLPMs were used for the models investigating relationships between SM frequency and other variables. However, given that SM addiction was only assessed beginning at Year 3, there are only two time points available for analyses, so CLPMs were used for those models.

All data analyses were conducted using R (Version 4.2.3). Data were screened for normality and descriptive statistics for all variables were computed. To test the hypotheses, RI-CLPM and CLPM models were built using the lavaan package (Rosseel, 2012), according to procedures outlined by Mulder and Hamaker (2021). Separate models were created for relationships between SM frequency and addiction and each of the other variables (prosocial behavior, family conflict, internalizing symptoms, externalizing symptoms), respectively. Thus, there were seven models in total (SMF and family conflict was not run due to missing data in the available ABCD dataset). The full information maximum likelihood method (FIML) was used to handle missing data. Given non-normality, maximum likelihood parameter (MLR) estimation was used. Additionally, given that there are potential developmental and gender differences in SMU and other study variables, time and gender equality constraints were tested for each model. More specific details about analytic procedures and all findings will be discussed in Chapter 3.

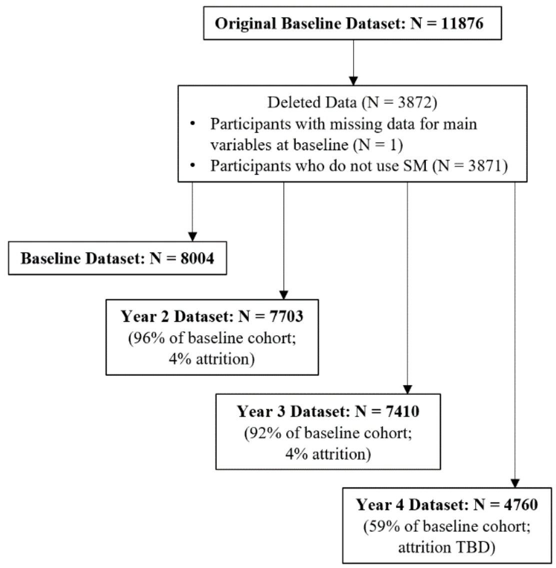
Chapter 3: Results

Preliminary Analyses

The original baseline dataset consisted of 11,876 participants. One participant's data were deleted because their data were missing for all of the variables of interest at Year 1. In addition, 3,871 participants' data were deleted because they answered zero or had missing data for SMU questions of interest (i.e., SMF and SM account ownership) for all four time points. The resulting dataset used for analyses consisted of 8,004 participants at Year 1; 7,703 at Year 2; 7,410 at Year 3; and 4,760 at Year 4. Attrition was relatively low. Given that data for the ABCD study are released on a rolling schedule, the dataset for Year 4 is not complete and contains 59% of the baseline sample. To determine whether there were any meaningful differences between the full sample and the partial sample that is available for Year 4, *t*-tests were conducted to investigate differences in demographic characteristics and variables of interest. Results of Welch's two sample *t*-test showed that there were significant differences between the Baseline and Year 4 samples for family income, SMF, and family conflict at Year 1. However, effect sizes were negligible to small. There were no significant differences between these two groups for prosocial behavior at Year 1. A consort diagram is presented in Figure 1.

Figure 1

Consort Diagram of Data Cleaning Procedures



Descriptive Analyses

Sociodemographics are presented in Table 1; the ABCD sample was intentionally recruited to be representative of national demographics. Multivariate normality was investigated using descriptive statistics and boxplots. Means and standard deviations of all variables at each time point are presented in Table 2. Participants generally reported low scores for all variables, which is expected for a non-clinical, community sample of young adolescents. SMF and SM addiction (SMA) increased over time. Family conflict and prosocial behavior remained relatively stable over time. Lastly, internalizing and externalizing scores also remained relatively stable over time.

At Year 1, all variables were positively skewed, except for prosocial behavior, which was negatively skewed. The directions of skew are expected given the scoring of each measure (i.e., higher scores on the PBS indicate more prosocial behavior, whereas the other measures use higher scores to indicate more problem behavior). Statistics seem to align with the sample, as it is a non-clinical, community population. Regarding outliers, the FES and PBS had a small number of outliers. SM frequency and the BPM scales had several outliers, indicating that there are more behaviors outside of the norm in these domains, which makes sense given the possibility of excessive SMU and clinical symptomatology (e.g., internalizing and externalizing disorders) in some participants. Importantly, however, the spreads of the outliers did not appear to suggest that there were subsets of the population that would need to be separated from the whole sample for analyses. To handle missing data and non-normality, FIML and MLR estimation were used for all models.

Table 1

Sociodemographic Characteristics of Participants at Baseline

Baseline Characteristic	*n*	%
Child Gender		
Female	4,042	50.5
Male	3,962	49.5
Child Race[a]		
White	3,798	47.4
Hispanic/Latino/Latina	1,782	22.3
Black	1,431	17.9
Asian	147	1.8
Other	846	10.6
Parent Education		
≤ 12th grade	610	7.6

Table 1 continued

Baseline Characteristic	*n*	%
High school degree	961	12.0
Some college	2,536	31.7
Bachelor's degree	2,074	25.9
Graduate degree	1,809	22.6
Not reported	14	0.2
Family Income		
< \$50,000	2,457	30.7
≤ \$50,000–\$100,000	1,993	24.9
≥ \$100,000	2,811	35.1
Not reported	743	9.3

[a]Races are mutually exclusive categories. The original ABCD questions included additional response options for race; the study also collapsed responses into these categories.

Table 2

Descriptive Statistics for all Variables at Each Time Point

Measure	*n*	*M*	*SD*	Range	Skew	Kurtosis
Participant age						
Year 1	8,004	9.98	0.62	8.92–11.08	-0.07	-1.26
Year 2	7,703	10.99	0.64	9.67–12.42	-0.07	-1.18
Year 3	7,410	12.06	0.66	10.58–14.00	0.01	-0.97
Year 4	4,760	12.94	0.64	11.42–14.50	-1.00	-1.06
Social media frequency						
Year 1	7,984	0.17	0.50	0–4	5.09	30.09
Year 2	7,693	0.33	0.70	0–4	3.38	12.47
Year 3	7,388	0.79	1.05	0–4	1.69	2.08
Year 4	4,751	1.11	1.16	0–4	1.18	0.42
Social media addiction						
Year 3	5,619	5.88	5.52	0–30	0.91	0.35
Year 4	4,161	7.07	5.82	0–30	0.59	-0.29
Family Environment Scale						
Year 1	7,985	2.06	1.95	0–9	0.93	0.22
Year 2	7,694	1.94	1.87	0–9	1.04	0.67
Year 3	7,388	1.99	1.85	0–9	0.97	0.47
Prosocial Behavior Scale						
Year 1	7,982	1.68	0.37	0–2	-1.09	0.76
Year 2	7,693	1.72	0.34	0–2	-1.29	1.69

Table 2 continued

Measure	*n*	*M*	*SD*	Range	Skew	Kurtosis
Prosocial Behavior Scale						
Year 3	7,391	1.70	0.37	0–2	-1.20	1.06
Year 4	4,756	1.71	0.35	0–2	-1.09	0.56
Internalizing symptoms						
Year 2	7,247	1.81	2.15	0–12	1.55	2.47
Year 3	7,102	1.93	2.29	0–12	1.56	2.42
Year 4	4,633	2.09	2.40	0–12	1.48	2.13
Externalizing symptoms						
Year 2	7,168	2.04	2.05	0–13	1.28	1.83
Year 3	7,032	2.15	2.05	0–13	1.11	1.28
Year 4	4,612	2.14	2.00	0–13	1.07	1.13

Note. Ranges for each variable are depicted within the header rows. The possible ranges are equal to the observed ranges for this dataset.

Detailed characteristics of adolescents' SMU were assessed at Years 3 and 4. TikTok was the most used platform, followed by Instagram and YouTube. Regarding privacy settings, a similar number of teens set their most used account to public and private. In response to the question about whether they had any SM accounts that they kept secret from their parents, most youth said "no" (72–83%). Bivariate correlations between variables at each time point are presented in Tables 3 through 6. At Year 1, there was a small correlation between higher SMF and more family conflict. There was a very small correlation between higher SMF and less prosocial behavior. At Year 2 when psychopathology was first assessed, there was a small but significant correlation between higher SMF and more internalizing and externalizing symptoms; the correlation between SMF and externalizing symptoms was slightly stronger. At Year 3 when SMA was first assessed, there was a moderate correlation between SMF and SMA. Correlations between SMA and other variables were relatively stronger than those with SMF. There were small correlations between more SMA and more family conflict and less prosocial behavior. There were moderate correlations between SMA and internalizing and externalizing symptoms. A table that includes bivariate correlations across time points is presented in Table A1 in Appendix A.

Table 3

Year 1 Bivariate Correlations

Variable	1	2	3
1. SMF1	–		
2. FES1	**.10**	–	
3. PBS1	*-.04*	**-.18**	–

Note. SMF1 = social media frequency at Year 1; FES1 = Family Environment Scale at Year 1; PBS1 = Prosocial Behavior Scale at Year 1. Coefficients with $p < .05$ and $p < .01$ are italicized; coefficients with $p < .001$ are bolded.

Table 4

Year 2 Bivariate Correlations

Variable	1	2	3	4	5
1. SMF2	–				
2. FES2	**.09**	–			
3. PBS2	*-.04*	**-.25**	–		
4. INT2	**.09**	**.27**	**-.13**	–	
5. EXT2	**.14**	**.43**	**-.32**	**.45**	–

Note. SMF2 = social media frequency at Year 2; FES2 = Family Environment Scale at Year 2; PBS2 = Prosocial Behavior Scale at Year 2; INT2 = internalizing symptoms at Year 2; EXT2 = externalizing symptoms at Year 2. Coefficients with p < *.05* and p < *.01* are italicized; coefficients with p < .001 are bolded.

Table 5

Year 3 Bivariate Correlations

Variable	1	2	3	4	5	6
1. SMF3	–					
2. SMA3	**.36**	–				
3. FES3	**.11**	**.22**	–			
4. PBS3	**-.05**	**-.12**	**-.22**	–		
5. INT3	**.14**	**.30**	**.24**	**-.05**	–	
6. EXT3	**.16**	**.29**	**.40**	**-.26**	**.40**	–

Note. SMF3 = social media frequency at Year 3; SMA3 = social media addiction at Year 3; FES3 = Family Environment Scale at Year 3; PBS3 = Prosocial Behavior Scale at Year 3; INT3 = internalizing symptoms at Year 3; EXT3 = externalizing symptoms at Year 3. Coefficients with $p < .05$ and $p < .01$ are italicized; coefficients with $p < .001$ are bolded.

Table 6

Year 4 Bivariate Correlations

Variable	1	2	3	4	5
1. SMF4	–				
2. SMA4	**.33**	–			
3. PBS4	-.00	**-.08**	–		
4. INT4	**.18**	**.31**	**-.06**	–	
5. EXT4	**.13**	**.26**	**-.28**	**.39**	–

Note. SMF4 = social media frequency at Year 4; SMA4 = social media addiction at Year 4; PBS4 = Prosocial Behavior Scale at Year 4; INT4 = internalizing symptoms at Year 4; EXT4 = externalizing symptoms at Year 4. Coefficients with $p < .05$ and $p < .01$ are italicized; coefficients with $p < .001$ are bolded.

Main Analyses

For the models that investigated SM frequency, the following procedures were used. The basic model was a full group RI-CLPM without any constraints across time points or gender groups. The time constraints model constrained regression coefficients of the cross-lagged paths to test if these relationships were invariant across time. A chi-square difference test was used to compare the constrained model to the basic model, and if it was significant, it implied that the cross-lagged effects differed over time, so time constraints were not tenable. The gender constraints model used a multiple group analysis with constraints across the two genders. Again, a chi-square difference test was used to compare the constrained model to the base model. If significant, it implied that the cross-lagged effects differed between genders, so gender constraints were not tenable. In this case, the multiple group model without constraints across groups was interpreted. For the models that investigated SM addiction, traditional CLPMs were used because addiction was only measured at time points three and four. RI-CLPMs require at least three time points of data, so those models could not be used. Time constraints were not tested, given that the models only used two time points. Gender constraints were tested. Fit indices for the RI-CLPMs are displayed in Table 7.

Table 7

Fit Indices for RI-CLPMs

Model	CFI	TLI	RMSEA	SRMR
PBS-SMF	.981	.942	.051	.021
FES-SMF	.997	.985	.028	.009
INT-SMF	.999	.984	.036	.007
EXT-SMF	-	-	-	-

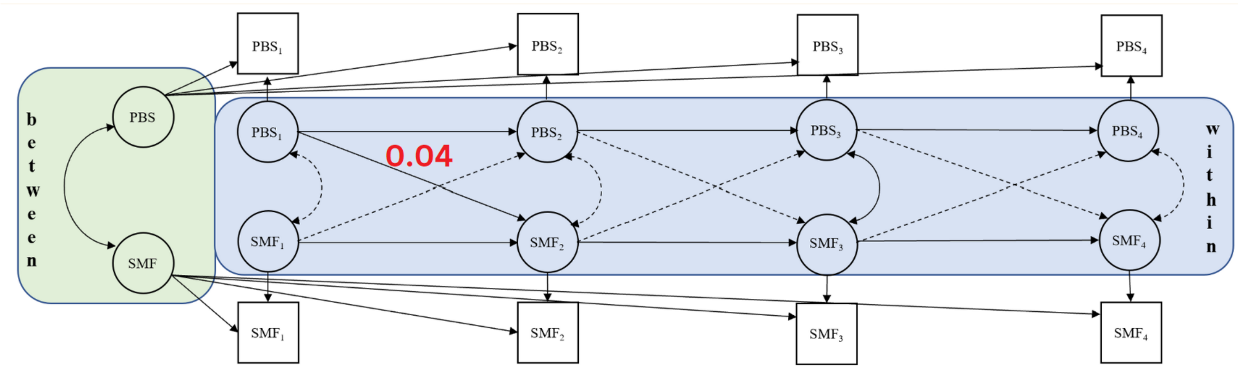
Note. Fit indices for CLPMs are not displayed because these models only used two time points and are just-identified. Fit indices for the externalizing symptoms model are also not displayed because time constraints were used, so the model was just-identified. Robust fit indices calculated using MLR estimation are displayed. CFI and TLI values .9 ≤ .95; RMSEA and SRMR values < .05 indicate good model fit (Hu & Bentler, 1998). Chi-square values are not reported, given that these are biased by the large sample size. PBS = Prosocial Behavior Scale; SMF = social media frequency; FES = Famly Environment Scale; INT = internalizing symptoms; EXT = externalizing symptoms.

Prosocial Behavior and SM Frequency

Time constraints were not tenable, but gender constraints were. Thus, the basic RI-CLPM that did not constrain cross-lagged effects by time or separate groups by gender was used for interpretation. Regarding between-person effects, there was a significant negative covariance between the random intercepts, suggesting that adolescents who reported more prosocial behavior, in general, also reported less SM frequency, in general. All autoregressive paths were significant. The valence of the autoregressive path from Year 1 to Year 2 for SM frequency was negative; whereas at later time points, it was positive. This indicates that an increase in SM frequency at Year 1 predicted a decrease in SM frequency at Year 2, but at later time points, increases in frequency predicted later increases. Covariance between variables at the same time point was significant only at Year 3, such that youth who reported more prosocial behavior at Year 3 concurrently reported less SM frequency. There was a difference in valence of the covariances at Year 1 (positive) compared to later time points (negative). Only one cross-lagged path was significant, such that children who reported more prosocial behavior as compared to their typical levels at Year 1 also reported more SM frequency at Year 2. The opposite path was not significant. A figure displaying significant paths for the SM frequency and prosocial behavior model is displayed in Figure 2; statistics for this model are displayed in Table 8.

Figure 2

Graphic of Social Media Frequency and Prosocial Behavior RI-CLPM



Note. Subscripts indicate time points. Bolded lines indicate significant paths, with standardized coefficients labelled in red in red for significant cross-lagged paths; dashed lines indicate paths that were not significant. PBS = Prosocial Behavior Scale; SMF = social media frequency.

Table 8

Statistics for Social Media Frequency and Prosocial Behavior RI-CLPM

Variable	*β*	*SE*	95% CI *LL*	95% CI *UL*	*p*	*B*
Autoregressive paths						
SMF1 → SMF2	*-0.16*	.13	-.53	-.01	.041	-.27
SMF2 → SMF3	**0.22**	.03	.30	.43	<.001	.36
SMF3 → SMF4	**0.42**	.02	.44	.52	<.001	.48
PBS1 → PBS2	*0.05*	.02	.01	.08	.010	.05
PBS2 → PBS3	**0.13**	.03	.10	.20	<.001	.15
PBS3 → PBS4	**0.22**	.02	.17	.25	<.001	.21

Table 8 continued

Variable	*β*	*SE*	95% CI		*p*	*B*
			LL	*UL*		
Covariances						
SMF1 – PBS1	0.01	.003	-.00	.01	.808	.00
SMF2 – PBS2	-0.01	.00	-.01	.01	.834	-.00
SMF3 – PBS3	*-0.04*	.00	-.02	-.01	.002	-.01
SMF4 – PBS4	-.01	.01	-.01	.01	.656	-.00
RISMF – RIPBS	**-0.12**	.00	-.01	-.00	<.001	-.01
Cross-lagged paths						
SMF1 → PBS2	0.00	.02	-.04	.04	.894	.00
SMF2 → PBS3	-0.03	.01	-.04	.00	.074	-.02
SMF3 → PBS4	-0.02	.01	-.02	.01	.255	-.01
PBS1→ SMF2	*0.04*	.04	.00	.16	.043	.08
Cross-lagged paths						
PBS2 → SMF3	-0.02	.06	-.20	.03	.144	-.09
PBS3 → SMF4	-0.01	.06	-.14	.10	.704	-.02

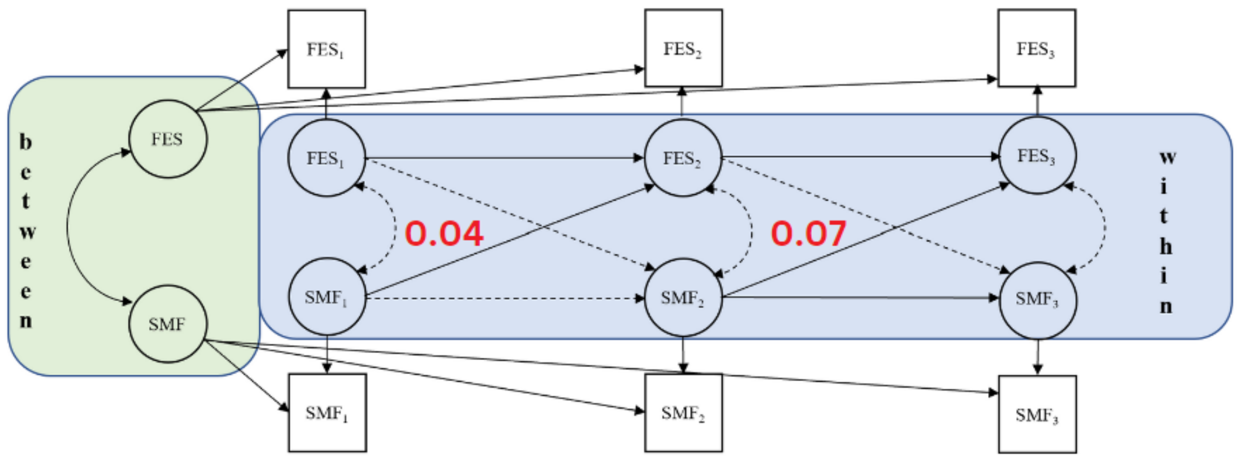
Note. Full group RI-CLPM without constraints. SMF = social media frequency; PBS = Prosocial Behavior Scale. Estimates with $p < .05$ and $p < .01$ are italicized; estimates with $p < .001$ are bolded.

Family Conflict and SM Frequency

Time constraints were tenable, but gender constraints were not tenable. Thus, the multiple group model that had constraints across time for the cross-lagged effects was used for interpretation. For both genders, autoregressive paths were significant at all time points, except for SM frequency from time point one to two. For both genders, there were significant positive covariances between the random intercepts, suggesting that adolescents who reported more family conflict, in general, also reported more SM frequency, in general. For girls, covariances between variables at the same time point were significant at all time points, such that children who reported more family conflict concurrently reported more SM frequency. However, there were no significant covariances for boys, other than the covariance between random intercepts. For girls, cross-lagged paths were significant in one direction, such that girls who reported more SM frequency as compared to their typical levels at initial time points also reported more family conflict at later time points. The opposite paths were not significant. For boys, there were no significant cross-lagged paths. The model testing associations between family conflict and SM addiction was not run because there were missing data for one of the required time points. Figures displaying significant paths for the SM frequency and family conflict models (male and female) are displayed in Figures 3 and 4; statistics for these models are displayed in Table 9.

Figure 3

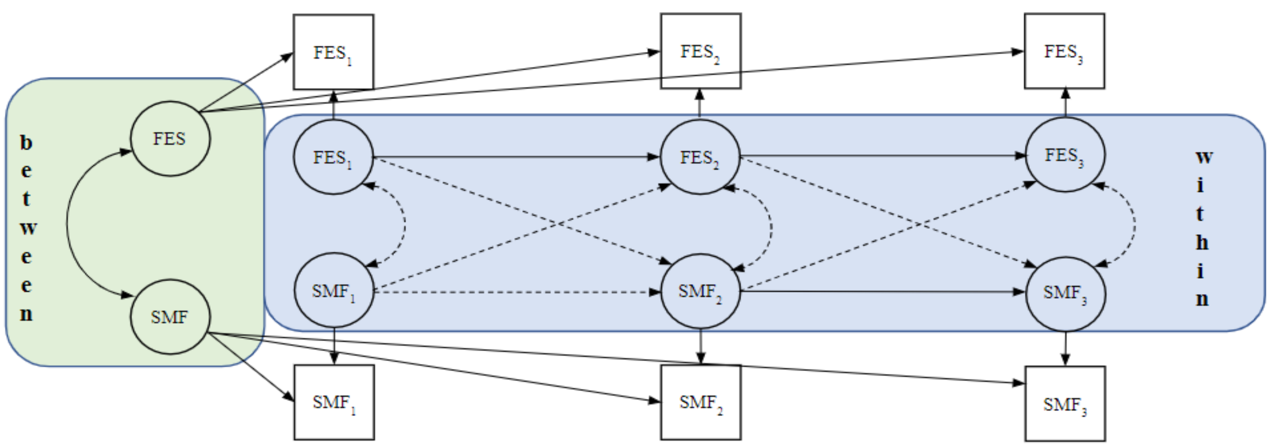
Graphic of Social Media Frequency and Family Conflict RI-CLPM (Female Model)



Note. Subscripts indicate time points. Bolded lines indicate significant paths, with standardized coefficients labelled in red for significant cross-lagged paths; dashed lines indicate paths that were not significant. FES = Family Environment Scale; SMF = social media frequency.

Figure 4

Graphic of Social Media Frequency and Family Conflict RI-CLPM (Male Model)



Note. Subscripts indicate time points. Bolded lines indicate significant paths; dashed lines indicate paths that were not significant. FES = Family Environment Scale; SMF = social media frequency.

Table 9

Statistics for Social Media Frequency and Family Conflict RI-CLPM

Females						
Variable	*β*	*SE*	95% CI		*p*	*B*
			LL	*UL*		
Autoregressive paths						
SMF1 → SMF2	-0.07	.21	-.53	.28	.535	-.13
SMF2 → SMF3	**0.24**	.04	.30	.46	<.001	.38
FES1 → FES2	**0.17**	.04	.09	.23	<.001	.18
FES2 → FES3	**0.17**	.04	.10	.25	<.001	.18
Covariances						
SMF1 – FES1	*0.08*	.02	.00	.09	.042	.04
SMF2 – FES2	**0.12**	.03	.06	.17	<.001	.11
SMF3 – FES3	**0.11**	.03	.11	.24	<.001	.18
RISMF – RIFES	**0.17**	.02	.03	.12	<.001	.07
Cross-lagged paths						
SMF1 → FES2	*0.04*	.06	.05	.27	.003	.16
SMF2 → FES3	*0.07*	.06	.05	.27	.003	.16
FES1 → SMF2	0.05	.01	-.00	.04	.061	.02
FES2 → SMF3	0.03	.01	-.00	.04	.061	.02

Table 9 continued

Males						
Variable	*β*	*SE*	95% CI		*p*	*B*
			LL	*UL*		
Autoregressive paths						
SMF1 → SMF2	-0.01	.12	-.24	.23	.968	-.01
SMF2 → SMF3	**0.19**	.05	.21	.42	<.001	.31
FES1 → FES2	**0.16**	.03	.10	.21	<.001	.16
FES2 → FES3	**0.16**	.03	.08	.21	<.001	.15
Covariances						
SMF1 – FES1	0.01	.02	-.03	.04	.693	.01
SMF2 – FES2	-0.00	.02	-.05	.04	.925	-.00
SMF3 – FES3	0.03	.02	-.01	.09	.112	.04
RISMF – RIFES	**0.25**	.02	.05	.12	<.001	.08
Cross-lagged paths						
SMF1 → FES2	0.02	.07	-.06	.20	.268	.07
SMF2 → FES3	0.03	.07	-.06	.20	.268	.07
FES1 → SMF2	-0.02	.01	-.02	.01	.492	-.01
FES2 → SMF3	-0.01	.01	-.02	.01	.492	-.01

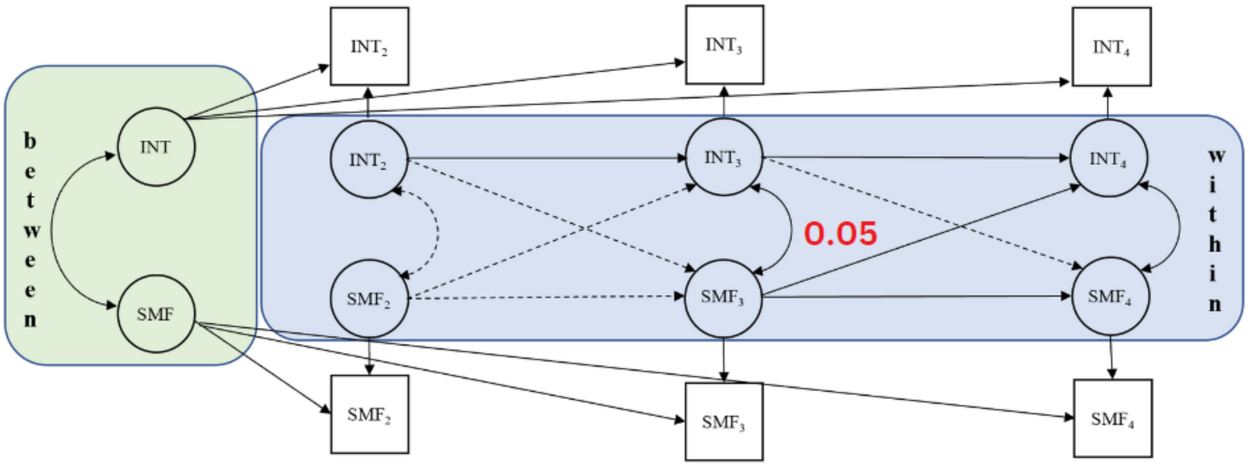
Note. Multiple group RI-CLPM with equality constraints across time for cross-lagged paths. SMF = social media frequency; FES = Family Environment Scale. Estimates with $p < .05$ and $p < .01$ are italicized; estimates with $p < .001$ are bolded.

Internalizing Symptoms and SM Frequency

Time constraints were not tenable, but gender constraints were. Thus, the basic RI-CLPM that did not constrain cross-lagged effects by time or separate groups by gender was used for interpretation. There was a significant positive covariance between the random intercepts, suggesting that adolescents who reported more internalizing symptoms, in general, also reported more SM frequency, in general. Nearly all autoregressive paths were significant, except for Year 2 to Year 3 for SM frequency. Covariances between variables at the same time point were significant at Years 3 and 4, but not Year 2. Children who reported more internalizing symptoms at those time points concurrently reported more SM frequency. Only one cross-lagged path was significant, such that children who reported more SM frequency as compared to their typical levels at Year 3 also reported more internalizing symptoms at Year 4. The opposite path was not significant. A figure displaying significant paths for the SM frequency and internalizing symptoms model is displayed in Figure 5; statistics for this model are displayed in Table 10.

Figure 5

Graphic of Social Media Frequency and Internalizing Symptoms RI-CLPM



Note. Subscripts indicate time points. Bolded lines indicate significant paths, with standardized coefficients labelled in red for significant cross-lagged paths; dashed lines indicate paths that were not significant. INT = internalizing symptoms; SMF = social media frequency.

Table 10

Statistics for Social Media Frequency and Internalizing Symptoms RI-CLPM

Variable	*β*	*SE*	95% CI		*p*	*B*
			LL	*UL*		
Autoregressive paths						
SMF2 → SMF3	-0.10	.16	-.54	.11	.193	-.21
SMF3 → SMF4	**0.32**	.03	.32	.43	<.001	.38
INT2 → INT3	**0.22**	.05	.15	.34	<.001	.25
INT3 → INT4	**0.37**	.03	.34	.46	<.001	.40
Covariances						
SMF2 – INT2	-0.08	.04	-.13	.02	.160	-.06
SMF3 – INT3	*0.09*	.05	.04	.25	.006	.15
SMF4 – INT4	**0.16**	.04	.24	.38	<.001	.31
RISMF – RIINT	**0.27**	.04	.12	.28	<.001	.20
Cross-lagged paths						
SMF2 → INT3	-0.07	.21	-.71	.11	.146	-.30
SMF3 → INT4	*0.05*	.05	.02	.21	.023	.11
INT2 → SMF3	-0.04	.02	-.06	.02	.355	-.02
INT3 → SMF4	0.01	.01	-.02	.03	.490	.01

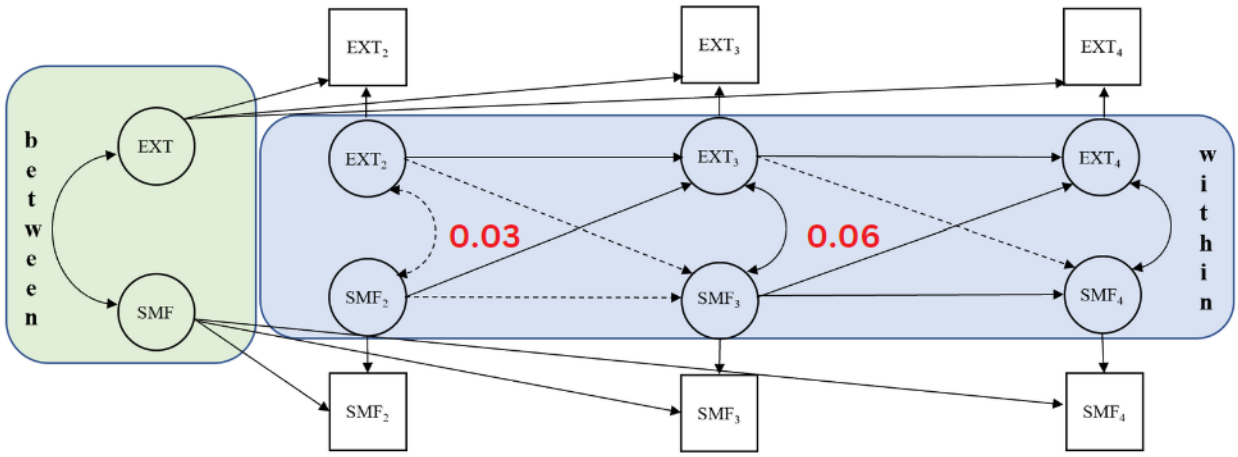
Note. Full group RI-CLPM without constraints. SMF = social media frequency; INT = internalizing symptoms. Estimates with $p < .05$ and $p < .01$ are italicized; estimates with $p < .001$ are bolded.

Externalizing Symptoms and SM Frequency

Both time and gender constraints were tenable. Thus, the RI-CLPM that constrained cross-lagged effects by time but did not separate groups by gender was interpreted. Effects were similar to those for internalizing symptoms and SM frequency. There was a significant positive covariance between the random intercepts, suggesting that adolescents who reported more externalizing symptoms, in general, also reported more SM frequency, in general. Nearly all autoregressive paths were significant, except for Year 2 to Year 3 for SM frequency. Covariances between variables at the same time point were significant at Years 3 and 4, but not time Year 2. Youth who reported more externalizing symptoms at those time points concurrently reported more SM frequency. Cross-lagged paths were significant in one direction, such that children who reported more SM frequency as compared to their typical levels at initial time points also reported more externalizing symptoms at later time points. The opposite paths were not significant. A figure displaying significant paths for the SM frequency and externalizing symptoms model is displayed in Figure 6; statistics for this model are displayed in Table 11.

Figure 6

Graphic of Social Media Frequency and Externalizing Symptoms RI-CLPM



Note. Subscripts indicate time points. Bolded lines indicate significant paths, with standardized coefficients labelled in red for significant cross-lagged paths; dashed lines indicate paths that were not significant. EXT = externalizing symptoms; SMF = social media frequency.

Table 11

Statistics for Social Media Frequency and Externalizing Symptoms RI-CLPM

Variable	β	*SE*	95% CI		*p*	*B*
			LL	*UL*		
Autoregressive paths						
SMF2 → SMF3	-0.11	.16	-.54	.08	.144	-.23
SMF3 → SMF4	**0.32**	.03	.32	.43	<.001	.37
EXT2 → EXT3	**0.23**	.04	.15	.30	<.001	.23
EXT3 → EXT4	**0.23**	.03	.16	.29	<.001	.23
Covariances						
SMF2 – EXT2	0.05	.02	-.01	.08	.117	.04
SMF3 – EXT3	**0.13**	.03	.11	.22	<.001	.17
SMF4 – EXT4	**0.10**	.03	.08	.19	<.001	.14
RISMF – RIEXT	**0.22**	.02	.13	.22	<.001	.17
Cross-lagged paths						
SMF2 → EXT3	*0.03*	.04	.02	.17	.013	.09
SMF3 → EXT4	*0.06*	.04	.02	.17	.013	.09
EXT2 → SMF3	0.03	.01	-.01	.04	.141	.02
EXT3 → SMF4	0.03	.01	-.01	.04	.141	.02

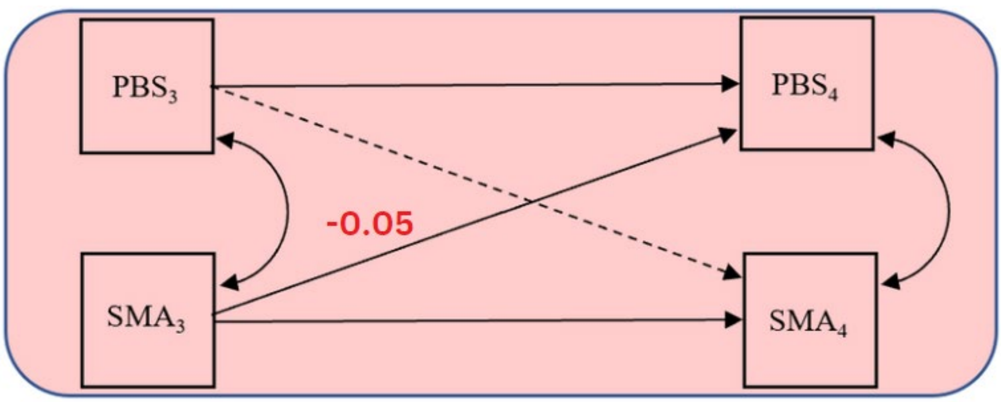
Note. Full group RI-CLPM with equality constraints across time for cross-lagged paths. SMF = social media frequency; EXT = externalizing symptoms. Estimates with $p < .05$ and $p < .01$ are italicized; estimates with $p < .001$ are bolded.

Prosocial Behavior and SM Addiction

For prosocial behavior and SMA, gender constraints were tenable, so the traditional CLPM was interpreted. Autoregressive paths at both time points were significant. Covariances were significant; children who reported more prosocial behavior concurrently reported less SMA. There was one significant cross-lagged path: children who reported more SMA at Year 3 also reported less prosocial behavior at Year 4. The opposite path was not significant. A figure displaying significant paths for the SM addiction and prosocial behavior model is displayed in Figure 7; statistics for this model are displayed in Table 12.

Figure 7

Graphic of Social Media Addiction and Prosocial Behavior CLPM



Note. Subscripts indicate time points. Bolded lines indicate significant paths, with standardized coefficients labelled in red for significant cross-lagged paths; dashed lines indicate paths that were not significant. PBS = Prosocial Behavior Scale; SMA = social media addiction.

Table 12

Statistics for Social Media Addiction and Prosocial Behavior CLPM

Variable	*β*	*SE*	95% CI		*p*	*B*
			LL	*UL*		
Autoregressive paths						
SMA3 → SMA4	**0.43**	.02	.41	.49	<.001	.45
PBS3 → PBS4	**0.47**	.02	.42	.48	<.001	.45
Covariances						
SMA3 – PBS3	**-0.13**	.03	-.31	-.20	<.001	-.25
SMA4 – PBS4	*-0.04*	.03	-.13	-.02	.012	-.07
Cross-lagged paths						
SMA3 → PBS4	*-0.05*	.00	-.01	-.00	.006	-.00
PBS3 → SMA4	-0.01	.25	-.69	.29	.420	-.02

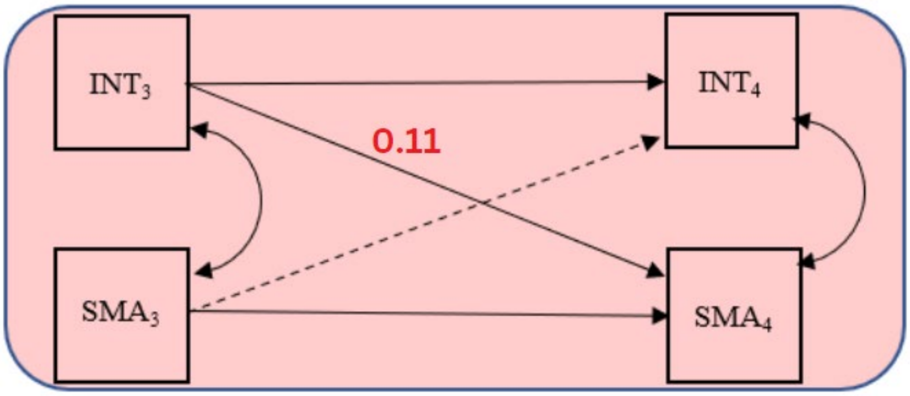
Note. Full group CLPM without constraints. SMA = Social media addiction; PBS = Prosocial Behavior Scale. Estimates with $p < .05$ and $p < .01$ are italicized; estimates with $p < .001$ are bolded.

Internalizing Symptoms and SM Addiction

Gender constraints were tenable, so the traditional CLPM was interpreted. Autoregressive paths were significant. Covariances were significant; children who reported more internalizing symptoms concurrently reported more SMA. There was one significant cross-lagged path: children who reported more internalizing symptoms at Year 3 also reported more SMA at Year 4. The opposite path was not significant. A figure displaying significant paths for the SM addiction and internalizing symptoms model is displayed in Figure 8; statistics for this model are displayed in Table 13.

Figure 8

Graphic of Social Media Addiction and Internalizing Symptoms CLPM



Note. Subscripts indicate time points. Bolded lines indicate significant paths, with standardized coefficients labelled in red for significant cross-lagged paths; dashed lines indicate paths that were not significant. INT = internalizing symptoms; SMA = social media addiction.

Table 13

Statistics for Social Media Addiction and Internalizing Symptoms CLPM

Variable	*β*	*SE*	95% CI		*p*	*B*
			LL	*UL*		
Autoregressive paths						
SMA3 → SMA4	**0.12**	.02	.38	.46	<.001	.42
INT3 → INT4	**0.58**	.02	.58	.65	<.001	.61
Covariances						
SMA3 – INT3	**0.30**	.20	3.41	4.19	<.001	3.80
SMA4 – INT4	**0.23**	.20	2.01	2.77	<.001	2.39
Cross-lagged paths						
SMA3 → INT4	0.03	.01	-.00	.03	.128	.01
INT3 → SMA4	**0.11**	.05	.19	.36	<.001	.27

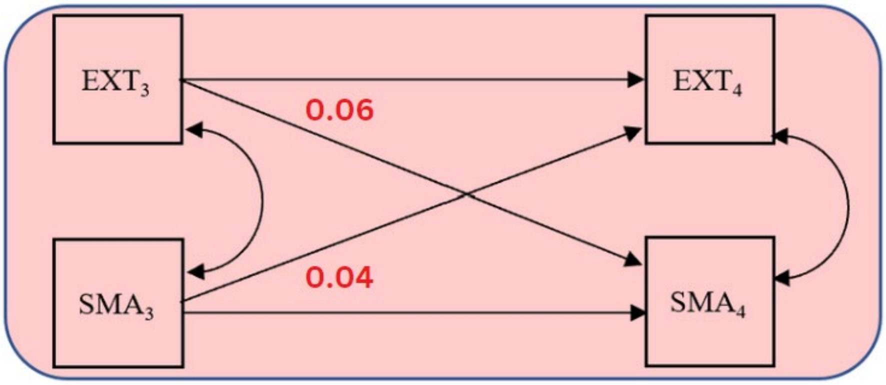
Note. Full group CLPM without constraints. SMA = Social media addiction; INT = internalizing symptoms. Estimates with $p < .05$ and $p < .01$ are italicized; estimates with $p < .001$ are bolded.

Externalizing Symptoms and SM Addiction

Gender constraints were tenable, so the traditional CLPM was interpreted. Autoregressive paths were significant. Covariances were significant; children who reported more externalizing symptoms concurrently reported more SM addiction. There was a significant bidirectional cross-lagged path: children who reported more externalizing symptoms at Year 3 also reported more SM addiction at Year 4, and vice versa. A figure displaying significant paths for the SM addiction and externalizing symptoms model is displayed in Figure 9; statistics for this model are displayed in Table 14.

Figure 9

Graphic of Social Media Addiction and Externalizing Symptoms CLPM



Note. Subscripts indicate time points. Bolded lines indicate significant paths, with standardized coefficients labelled in red for significant cross-lagged paths; dashed lines indicate paths that were not significant. EXT = externalizing symptoms; SMA = social media addiction.

Table 14

Statistics for Social Media Addiction and Externalizing Symptoms CLPM

Variable	*β*	*SE*	95% CI		*p*	*B*
			LL	*UL*		
Autoregressive paths						
SMA3 → SMA4	**0.41**	.02	.40	.48	<.001	.44
EXT3 → EXT4	**0.59**	.02	.55	.61	<.001	.58
Covariances						
SMA3 – EXT3	**0.30**	.19	2.99	3.73	<.001	3.36
SMA4 – EXT4	**0.20**	.16	1.33	1.97	<.001	1.65
Cross-lagged paths						
SMA3 → EXT4	*0.04*	.01	.00	.03	.021	.02
EXT3 → SMA4	**0.06**	.05	.08	.27	<.001	.17

Note. Full group CLPM without constraints. SMA = Social media addiction; EXT = externalizing symptoms. Estimates with $p < .05$ and $p < .01$ are italicized; estimates with $p < .001$ are bolded.

Chapter 4: Discussion

Adolescence is a time of many biological, psychological, and social changes. During this developmental period, individuals may experience mental health challenges and difficulties in social relationships. In recent years, SM has fundamentally changed the way that adolescents interact with the world. Additionally, the COVID-19 pandemic has also changed the environment substantially. Existing research on associations between SMU, psychopathology, and social functioning is limited by methodological factors. Specifically, many studies have investigated older adolescents cross-sectionally using similar analytic methods. Fewer studies have used robust analyses to examine within-person associations using diverse samples, over the span of a few years. It is particularly important to consider the use of within-person analyses for the study of SMU in adolescents, given that individual differences could be driving existing significant findings and overstating or obscuring the true nature of relationships between variables. Additionally, researchers often only focus on the effect of SMU on certain outcomes, like depression and sleep; however, fewer studies have investigated other aspects of functioning, like externalizing symptoms and prosocial behavior. Furthermore, some studies have begun to investigate the concept of SMA; however, more research is needed. Thus, the current study sought to investigate relationships between SMU, both frequency and addictive behavior, social functioning, including prosocial behavior and family conflict, and psychopathology, namely internalizing and externalizing symptoms.

Hypotheses included that there would be bidirectional relationships between higher levels of SM frequency and addiction and higher levels of most of the other variables, including family conflict and externalizing symptoms. Relationships were hypothesized to be more complicated for prosocial behavior and internalizing symptoms. For prosocial behavior, it was hypothesized that there would be bidirectional relationships between higher levels of SM frequency and *more* prosocial behavior, but bidirectional relationships between higher levels of SM addiction and less prosocial behavior. For internalizing symptoms, it was hypothesized that there would *not* be a significant relationship with SMF, but that there would be a significant, bidirectional relationship between higher SMA and more symptoms.

Obtained correlations were expected given the current study's hypotheses, except for the relationship between SMF and prosocial behavior, which is the opposite of what was anticipated. The results showed that SMF was *negatively* correlated with prosocial behavior, for the first three time points but not at Year 4. Prosocial behavior was significantly correlated with SMA at Year 4 though. For most time points, the strongest bivariate correlations with SMF were externalizing symptoms, internalizing symptoms, family conflict, and then less prosocial behavior. The strongest relationships with SMA, however, were internalizing symptoms first then externalizing symptoms, family conflict, and less prosocial behavior. Additionally, the strength of correlations was stronger for relationships between SMA and other variables compared with those between SMF. This discrepancy in correlations' strength between SM frequency and addiction aligns with previous literature (Boer et al., 2020) and this study's hypotheses, suggesting that more impairment is associated with SMA compared to SMF alone.

For nearly all cross-lagged analyses, relationships were unidirectional, with the SM variable predicting changes in the other variable. There were a few exceptions to this. For the relationship between prosocial behavior and SM frequency, increases in prosocial behavior predicted increases in SM frequency. Additionally, the relationship was bidirectional for the CLPM for SM addiction and externalizing symptoms. Taken together, it appears that prosocial behavior and externalizing symptoms were the only variables that predicted changes in SM use at later time points, whereas the other relationships went in the reverse direction. The results of the RI-CLPMs and CLPMs will be discussed in more detail below.

Prosocial Behavior

For prosocial behavior, the results of the cross-lagged models aligned with hypotheses, but only unidirectionally. For frequency, the cross-lagged paths showed that more prosocial behavior at Year 1 predicted more SMF at Year 2. However, the effect size was small. Interestingly, the covariance of the random intercepts had the inverse effect, such that in general, adolescents who reported more prosocial behavior also reported less SMF. This discrepancy in the between-person effects versus the within-person effects suggests that individual differences (e.g., personality differences in extraversion) is likely driving the negative relationship, which aligns with dispositional theories of prosocial behavior. For example, adolescents who are more extraverted (and thus more prosocial; Wolters et al., 2014) may be engaging in more in-person social activities rather than using SM frequently. However, the within-person finding suggests that for all adolescents, regardless of individual differences, being more prosocial leads to more SMF. This could be because for adolescents who would like to engage in more prosocial activities, SM applications are a natural place to connect with, empathize with, and advocate for others.

The cross-lagged effect goes in the opposite direction of previous longitudinal studies that have found that SMU predicts prosocial behavior (e.g., empathy; Vossen & Valkenburg, 2016). However, the participants in that study were older adolescents. For the current study, the finding being significant in this particular direction and only from Year 1 to Year 2 may be reflective of developmental changes. Participants were 9 to 10 years old at Year 1, which may have been during pre-puberty and the beginning of puberty for some, when peer interactions are becoming particularly salient. Changes also occurred at Year 2 when children were 10–11 years old, which was also likely a transitional period for many participants as they advanced to middle school. Indeed, previous studies have found that levels of prosocial behavior fluctuate during adolescence (Van der Graff et al., 2018). Furthermore, this time point could have been when many participants started using social media for the first time. Interestingly, the covariances between SMF and prosocial behavior were not significant at Years 1 and 2, but the cross-lagged effect was significant. This also points to developmental changes and suggests that there may be mediating factors in this relationship that take time to have an effect. Covariance was significant at Year 3 (data collected from 2018 to 2021), however, perhaps suggesting that when pandemic restrictions were strongest and in-person interactions declined, there was a more concurrent relationship between more SMU and less prosocial behavior. It is surprising that there were no gender differences found for this model, given that previous studies have found gender differences in the trajectories of prosocial behavior during adolescence (Van der Graaff et al., 2018).

For the prosocial behavior and SMA CLPM, findings were opposite to the SMF findings, such that SMA was the predictor, and it resulted in *less* prosocial behavior. This partially aligned with the hypothesis. It was also significant at a different time point compared to SMF; however, the CLPM did not include time points one and two (since the addiction measure was not used at those time points). Specifically, more SMA at Year 3 predicted *less* prosocial behavior at Year 4. This may suggest that while increases in SM frequency may not predict either negative or positive subsequent changes in prosocial behavior; increases in SM addiction predict negative changes. Effect sizes were also larger for relationships between SMA and prosocial behavior compared with those for SMF and prosocial behavior. This discrepancy aligns with literature suggesting that addictive SM usage is associated with more impairment than high frequency usage (Boer et al., 2020). Addictive behaviors may lead to withdrawal from in-person social interactions and in turn, less prosocial behavior. Importantly, data for Years 3 and 4 were collected during the COVID-19 pandemic. Research suggests that SMA and psychosocial functioning were worse during the pandemic (Muzi et al., 2021), so this finding provides further evidence to support links between these variables in the context of the pandemic. It is important to note, however, that the CLPM does not account for within-person differences, so this significant effect could reflect both between-person and within-person differences. Thus, it could be that those individuals who are more prone to addictive behaviors at baseline are also less prosocial in general.

Family Conflict

For family conflict, the results for SM frequency aligned with the hypotheses unidirectionally, but only for girls. For boys, there were no significant cross-lagged effects. For girls, more SM frequency predicted more family conflict. This gender difference aligns with the finding of Sampasa-Kanyinga and colleagues (2020) that there were more consistent relationships between more frequent SMU and more negative parent-child relationship functioning for girls compared to boys. However, it contradicts other studies that have not found gender differences in relationships between similar variables (Vannucci & Ohannessian, 2019; Wartberg et al., 2020). These studies did not investigate long term longitudinal relationships, and they did not use analyses that parse apart between and within person differences like the current study. It could be that at the whole group level, gender differences are masked because there are other individual differences that contribute to variance that affect both genders. However, when these variables are examined at the individual level, SM frequency has a greater impact on family conflict for girls compared to boys. This is supported by the finding that covariances of the random intercepts were significant for both girls and boys; however, there was a gender difference in the cross-lagged effects.

This gender difference could potentially be explained by the tendency for girls to engage in more social support seeking and co-rumination than boys (Zimmermann & Iwanski, 2014). It could be that girls are engaging more in these activities on SM, resulting in strengthening of peer relationships and weakening of family relationships, and thus more family conflict at the later time point. If this was the case, we may expect a gender difference in the relationship between SMF and prosocial behavior as well; however, the measure of prosocial behavior in this study did not differentiate between prosocial behavior towards peers and behavior towards family members. Furthermore, the effect sizes increased over time, such that the effect size of the relationship between SMF and FES for girls was small from Year 1 to Year 2 but medium from Year 2 to Year 3. This could be due to developmental changes in attachment relationships over time (i.e., parents becoming "de-idealized" [Steinberg, 2005] and less effective at helping adolescents regulate emotions [Hostinar et al., 2015]). There was no model run for family conflict and SMA due to missing data.

Internalizing Symptoms

For internalizing symptoms, the hypothesis about SM frequency that there would *not* be a within-person association was not supported. There was a significant cross-lagged path from Year 3 to Year 4, with more SM frequency predicting more internalizing symptoms. This effect only being significant at the last time point may indicate developmental change, such that for middle adolescents, the connection between SMU and internalizing symptoms may be more salient. This contradicts Boer and colleagues' study, which did not find a significant link between these variables. Puukko and colleagues (2020) also found a significant association, but in the opposite direction. However, that study only focused on active SMU (e.g., communicating with others), and data were collected from 2014 to 2018, when older social networking sites like Facebook were more common. It could be that results for the current study went in the opposite direction because our frequency measure did not distinguish between active and passive use (e.g., scrolling through others' feeds), and SM applications like Instagram are more common now. Indeed, there have been studies that suggest that passive use is more closely related to internalizing symptoms, and that use of SM applications with more visual content is related to more negative outcomes including negative body image (Vandenbosch et al., 2022) and SMA (Marengo et al., 2022). In examining the covariances, links between internalizing symptoms and SMF appeared to become stronger over time; this was not the case for prosocial behavior and family conflict.

For addiction, the hypothesis was supported unidirectionally. However, the effect went in the opposite direction as frequency, similarly to the different patterns observed for prosocial behavior and SMF and SMA. More internalizing symptoms at Year 3 predicted more SM addiction at Year 4. However, given that the addiction analysis was conducted using a CLPM, this finding could have been driven by both between-person and within-person differences. As mentioned, data for Years 3 and 4 were collected during the COVID-19 pandemic. In line with findings from Cauberghe and colleagues (2021), it could be that individuals who experience increases in symptoms of anxiety and depression (potentially due to environmental factors associated with the pandemic) turn to SM to cope; however, it may not result in a decrease of symptoms for certain adolescents (e.g., ones experiencing more loneliness compared to anxiety) but rather an exacerbation and thus a cycle of maladaptive behavior that ultimately increases levels of SMA. In some ways, this aligns with the “poor get poorer” model; however, moderation analyses would be needed to further clarify these links. It was surprising that there were no gender differences found for these models, given that there are gender differences in rates of internalizing symptoms in adolescents (Twenge et al., 2018).

Externalizing Symptoms

For externalizing symptoms, the frequency hypothesis was supported unidirectionally; SM frequency predicted more externalizing symptoms for both time points. It is interesting that there were more consistent relationships between externalizing symptoms and SMF compared to internalizing symptoms and SMF, given that much of the SM literature has focused on internalizing symptoms. However, this does align with previous studies that have also used ABCD data (Guerrero et al., 2019; Paulus et al., 2019). This result also supports previous research that has found relationships between SMU and risky behaviors in adolescents (Vannucci & Ohannessian, 2019). A unique finding of this model was that although effect sizes of covariances between variables increased in strength over time, equality constraints on time were tenable for the cross-lagged associations. This may indicate that although there may be developmental differences when comparing each time point individually, the longitudinal relationship between SMF and externalizing symptoms is relatively stable over time. However, there are stable relationships between SMF and externalizing symptoms over time, which was not the case for models investigating the other variables (prosocial behavior, family conflict, externalizing symptoms).

For addiction, the bidirectional hypothesis was supported, such that more SMA predicted more externalizing symptoms *and* more externalizing symptoms predicted more SMA. Again, this finding supports the notion that SMA is more impairing than SMF alone. Given that this analysis was conducted using CLPM, and so significant results may be driven by individual differences, the finding may be explained by characteristics of children with more externalizing symptoms. Specifically, adolescents with externalizing disorder have high reward sensitivity (Carlson et al., 2013), so they may be more prone to use SM more to obtain "likes," which have been shown to activate brain reward processing areas (Sherman et al., 2018). Consequently, they may be prone to develop more impairment associated with SMA. Similarly to the results of internalizing symptoms and SMA, this may align with the "poor get poorer" model, but more moderation studies are needed.

Clinical Implications

The findings of this study have several clinical implications. First, adolescents and their families should be educated about SM and both its potential advantages and disadvantages. In May 2023, the American Psychological Association released a report titled *Health Advisory on Social Media Use in Adolescence* that includes evidence-based recommendations for those who care for, work with, and create policies relevant to adolescents (American Psychological Association, 2023). Their recommendations fit well with the findings of the current study. Given that there are so many biological, psychological, and social changes that occur during the course of adolescence, developmental appropriateness should be one of the first considerations. Indeed, the results of the current study showed that for most models, there were differences across time, suggesting that the impacts of SMU on adolescent functioning and vice versa changes as individuals mature. Additionally, autonomy is important to foster during adolescence. Thus, parents should work with adolescents and consider their input when making decisions about SMU. Additionally, parental monitoring should be stricter for younger versus older adolescents.

"Social media literacy," or education about safe and productive SMU, should be prioritized (American Psychological Association, 2023, p. 8). Adolescents should be informed about the differences between different types of platforms and their potential harmful effects, especially if they have pre-existing mental health conditions, like internalizing or externalizing disorders. Given the gender differences found in this study, providers and parents should be aware that girls may be more susceptible to the negative effects of SMU, especially regarding family conflict and SMA. Providers, teachers, and parents should be aware of the signs of SMA and intervene if they notice that adolescents are using SM too frequently, missing out on in-person activities because of it, or engaging in deceptive behavior to use it. Additionally, given the bidirectional findings linking SMA to externalizing symptoms, parents and teens should be aware that SMA could lead to more risky behaviors, *and* this relationship could go in the other direction, such that teens who are more prone to conduct problems and other addictions (e.g., drug and alcohol use) may also be more susceptible to becoming addicted to SM. In the same vein, it is important that adolescents and parents be educated about the potential positive aspects of SMU, including opportunities for prosocial behavior. In both online and offline contexts, positive peer and family relationships should be prioritized, as these could be protective factors against a variety of negative outcomes during adolescence.

Limitations and Future Directions

Although the current study made several improvements in methodology compared to previous studies, it has notable limitations. First, like many other studies investigating SMU, it utilized self-report measures, so reporter bias is a possibility. This study was limited because participants were not included if they did not report using SM during any of the four time points, and this excluded over 30% of ABCD participants. However, it is important to note that since this sample was comprised of early adolescents, it is reasonable that there were a portion of youth that did not use SM at all, and it is also possible that they were using SM and did not report it. It would be beneficial for future research to explore differences between SM users and non-users, or those who start using SM later in adolescence. Additionally, given that the response options for SM frequency were capped at 4 hours, there could have been a ceiling effect for this variable. The ABCD study is piloting objective measurement of technology use; future studies should utilize these data to investigate these relationships. Furthermore, although this study did not include multiple reporters, future studies could utilize parent and peer reports to investigate these issues from multiple perspectives. While the ABCD study planned to recruit a nationally representative sample, the final participant inclusion criteria introduced some selection bias. This resulted in a less diverse sample than anticipated.

Whereas this study provided insight into relationships between SMU and other variables in early and middle adolescence, future research could capture additional, later time points to further investigate the trajectories of these phenomena, especially SMA to provide a longer-term assessment of its associated impairment. Given that at the time of the current study, there were only two time points of SMA data available, RI-CLPM analyses could not be conducted, so traditional CLPMs were used. Thus, between and within person differences could not be parsed apart for the addiction analyses. It will be important to investigate SMA with RI-CLPMs when more time points of data are available. Additionally, as previously mentioned, this study may have not captured constructs specifically enough to produce meaningful findings, particularly for social functioning. It would be helpful to incorporate other measures of social functioning, like relationship quality, and target parent-child and peer relationships specifically. Lastly, this study treated internalizing symptoms, externalizing symptoms, and SMA as separate constructs;

however, measurement covariance limits conclusions that can be drawn about unique effects. Thus, while this study focused on broad relationships between variables, it would be helpful to additionally assess for mediating and moderating processes.

Conclusions

The current study investigated relationships between SMU (frequency and addictive behavior), social functioning prosocial behavior and family conflict), and psychopathology (internalizing and externalizing symptoms). Overall, results showed that within-person changes in SM frequency and addiction predicted changes in most of the other variables, and SMA was more consistently and strongly related to other variables than SMF. Notably, externalizing symptoms appeared to have a more consistent relationship with SMA than other variables. This study contributes to the literature on SMU in adolescence in that it provides a detailed examination of both between-person and within-person effects, from early- through mid-adolescence, in a nationally representative American sample. It is also unique in that it adds to the literature on adolescent functioning during the COVID-19 pandemic. Clinically, it highlights the importance of SM literacy and screening for potentially addictive behaviors on SM, especially in adolescents with externalizing symptoms. Future research should continue to expand upon these findings by investigating potential mediators and moderators and investigating how these relationships may change as the ABCD sample ages into later adolescence and early adulthood.

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APPENDICES

Appendix A: Bivariate Correlations for All Time Points

Table A1

Bivariate Correlations Between Variables for all Time Points

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1. SMF1																			
2. PBS1	*-.04*																		
3. FES1	**.10**	**-.18**																	
4. SMF2	**.27**	-.00	**.05**																
5. PBS2	**-.04**	**.38**	**-.18**	*-.04*															
6. FES2	**.08**	**-.15**	**.46**	**.09**	**-.25**														
7. INT2	**.04**	**-.06**	**.17**	**.09**	**-.13**	**.27**													
8. EXT2	**.11**	**-.18**	**.30**	**.14**	**-.32**	**.43**	**.45**												
9. SMF3	**.19**	.01	**.05**	**.33**	-.03*	**.05**	**.07**	**.09**											
10. SMA3	**.10**	**-.06**	**.11**	**.17**	**-.09**	**.15**	**.22**	**.20**	**.36**										
11. PBS3	**-.05**	**.33**	**-.15**	**-.06**	**.43**	**-.19**	**-.07**	**-.24**	**-.05**	**-.12**									
12. FES3	**.08**	**-.13**	**.38**	**.10**	**-.19**	**.48**	**.21**	**.36**	**.11**	**.22**	**-.22**								
13. INT3	*.03*	-.02	**.12**	**.08**	**-.06**	**.18**	**.51**	**.24**	**.14**	**.30**	**-.05**	**.24**							
14. EXT3	**.08**	**-.15**	**.25**	**.13**	**-.22**	**.30**	**.29**	**.58**	**.16**	**.29**	**-.26**	**.40**	**.40**						
15. SMF4	**.17**	*.04*	.03	**.31**	.03*	.03*	.04*	*.04*	**.44**	**.21**	-.01	**.07**	**.08**	**.08**					
16. SMA4	**.16**	-.03*	**.07**	**.15**	**-.05**	**.07**	**.19**	**.16**	**.21**	**.41**	**-.06**	**.12**	**.22**	**.18**	**.33**				
17. PBS4	-.01	**.29**	**-.15**	-.03*	**.37**	**-.20**	**-.13**	**-.25**	-.02	**-.09**	**.47**	**-.21**	**-.10**	**-.24**	-.00	**-.08**			
18. INT4	**.05**	.03*	**.08**	**.10**	-.02	**.10**	**.41**	**.20**	**.13**	**.21**	.00	**.15**	**.57**	**.24**	**.18**	**.31**	**-.06**		
19. EXT4	**0.07**	**-0.10**	**0.20**	**0.10**	**-0.17**	**0.27**	**0.25**	**0.50**	**0.12**	**0.21**	**-0.17**	**0.34**	**0.29**	**0.59**	**0.13**	**0.26**	**-0.28**	**0.39**	

Note. SMF = social media frequency; SMA = social media addiction; FES = Family Environment Scale; PBS = Prosocial Behavior Scale; INT = internalizing symptoms; EXT = externalizing symptoms. Coefficients with $p < .05$ and $p < .01$ are italicized; coefficients with $p < .001$ are bolded.

Appendix B: Data Access Approval

NIMH Data Archive: Adolescent Brain Cognitive Development Permission Approved (Schmitt, Request 9456)

1 message

NIMHDataArchive@mail.nih.gov <NIMHDataArchive@mail.nih.gov> Mon, Aug 30, 2021 at 1:17 PM
To: aschmi36@emich.edu, egoff4@emich.edu, jlawler1@emich.edu
Cc: ndahelp@mail.nih.gov

Dear Aidan Schmitt and Jamie Lawler,

Congratulations! Your request to access to data in the Adolescent Brain Cognitive Development permission group in the NIMH Data Archive (NDA) has been approved by an NIH Data Access Committee. Your data access will expire on 08/30/2022. Permission to access shared data in NDA is valid for a period of one year.

Comments from the Data Access Committee: No comments provided

You and your institution are responsible for adhering to the terms of data use as outlined in the NDA Data Use Certification (DUC).

If you are not the lead recipient on this DUC, you must agree to the NDA terms of data use by logging into the NDA web application at https://nda.nih.gov/, where you will be immediately presented with the terms for acceptance. *You are not authorized to access Adolescent Brain Cognitive Development data until you've done so.*

A summary of key points is provided below:

- *Data Distribution:* You cannot distribute NDA data to unauthorized individuals or third-party systems. This includes raw data from any individual study participant and derived subject-level data if the derived data can aid in the re-identification of a participant.

- *Collaboration:* You may share NDA data with authorized individuals for the purpose of collaboration on research projects.

- *Re-Identification:* You cannot attempt to re-identify individual study participants or their relatives.

- *Research Use Reporting*: You must create and share an NDA Study for each publication, computational pipeline, or other public disclosure of results from the analysis of NDA data. In each of these publications, the appropriate acknowledgement(s) must be made. See https://nda.nih.gov/get/manuscript-preparation.html for guidance.

- *Data Deletion*: You must permanently delete NDA data from all machines when your research is completed or the DUC expires, whichever comes first. You may only retain encrypted copies of the minimum data necessary to comply with institutional scientific data retention policies.

Please contact the NDA Help Desk at NDAHelp@mail.nih.gov with any questions.

Regards,

NIMH Data Archive (NDA) Staff
NDAHelp@mail.nih.gov
301-443-3265

NDA Notification ID:83092

Appendix C: Data Access Renewal

NIMH Data Archive: Adolescent Brain Cognitive Development Permission Approved (Schmitt, Request 12461)

5 messages

NIMHDataArchive@mail.nih.gov <NIMHDataArchive@mail.nih.gov> Mon, Aug 8, 2022 at 11:26 AM
To: aschmi36@emich.edu, egoff4@emich.edu, jlawler1@emich.edu
Cc: ndahelp@mail.nih.gov

Dear Aidan Schmitt and Jamie Lawler,

Congratulations! Your request to access to data in the Adolescent Brain Cognitive Development permission group in the NIMH Data Archive (NDA) has been approved by an NIH Data Access Committee. Your data access will expire on 08/08/2023. Permission to access shared data in NDA is valid for a period of one year.

Comments from the Data Access Committee: No comments provided

You and your institution are responsible for adhering to the terms of data use as outlined in the NDA Data Use Certification (DUC).

If you are not the lead recipient on this DUC, you must agree to the NDA terms of data use by logging into the NDA web application at https://nda.nih.gov/, where you will be immediately presented with the terms for acceptance. *You are not authorized to access Adolescent Brain Cognitive Development data until you've done so.*

A summary of key points is provided below:

- *Data Distribution:* You cannot distribute NDA data to unauthorized individuals or third-party systems. This includes raw data from any individual study participant and derived subject-level data if the derived data can aid in the re-identification of a participant.
- *Collaboration:* You may share NDA data with authorized individuals for the purpose of collaboration on research projects.
- *Re-Identification:* You cannot attempt to re-identify individual study participants or their relatives.
- *Research Use Reporting*: You must create and share an NDA Study for each publication, computational pipeline, or other public disclosure of results from the analysis of NDA data. In each of these publications, the appropriate acknowledgement(s) must be made. See https://nda.nih.gov/get/manuscript-preparation.html for guidance.
- *Data Deletion*: You must permanently delete NDA data from all machines when your research is completed or the DUC expires, whichever comes first. You may only retain encrypted copies of the minimum data necessary to comply with institutional scientific data retention policies.

Please contact the NDA Help Desk at NDAHelp@mail.nih.gov with any questions.

Regards,

NIMH Data Archive (NDA) Staff
NDAHelp@mail.nih.gov

NDA Notification ID:119666

Appendix D: Demographics Survey (Parent Report; Stover et al., 2010)

1. You are the:
    a. *1 = Childs Biological Mother; 2 = Childs Biological Father; 3 = Adoptive Parent; 4 = Child's Custodial Parent; 5 = Other*
2. How old is the child?
3. What sex was the child assigned at birth, on the original birth certificate?
    a. *1 = Male; 2 = Female; 3 = Intersex-Male; 4 = Intersex-Female; 999 = Don't know; 777 = Refuse to answer*
4. What race do you consider the child to be?
    a. Original response options: *White, Black/African American, American Indian or Alaska Native, Asian Indian, Chinese, Filipino, Japanese, Korean, Vietnamese, Other Asian, for example, Hmong, Laotian, Thai, Pakistani, Cambodian, and so on, Native Hawaiian, Guamanian or Chamorro, Samoan, Other Pacific Islander, for example, Fijian, Tongan, and so on, Some other race, Refuse to answer, Don't know*
    b. Categories created by ABCD: 1 = *White*; 2 = *Black*; 3 = *Hispanic*; 4 = *Asian*; 5 = *Other*
5. Do you consider the child Hispanic/Latino/Latina?
6. What is the highest grade or level of school you have completed or the highest degree you have received?
    a. *0 = Never attended/Kindergarten only; 1 = 1st grade; 2 = 2nd grade; 3 = 3rd grade 3.er grado ; 4 = 4th grade; 5 = 5th grade; 6 = 6th grade; 7 = 7th grade; 8 = 8th grade; 9 = 9th grade; 10 = 10th grade; 11 = 11th grade; 12 = 12th grade;*

13 = High school graduate; 14 = GED or equivalent Diploma; 15 = Some college; 16 = Associate degree: Occupational; 17 = Associate degree: Academic Program; 18 = Bachelor's degree (ex. BA); 19 = Master's degree (ex. MA); 20 = Professional School degree (ex. MD); 21 = Doctoral degree (ex. PhD); 777 = Refused to answer

7. How much did you earn, before taxes and other deductions, during the past 12 months?
    a. *1 = Less than $5,000; 2 = $5,000 through $11,999; 3 = $12,000 through $15,999; 4 = $16,000 through $24,999; 5 = $25,000 through $34,999; 6 = $35,000 through $49,999; 7 = $50,000 through $74,999; 8 = $75,000 through $99,999; 9 = $100,000 through $199,999; 10 = $200,000 and greater; 777 = Refuse to answer; 999 = Don't know*

Appendix E: Screen Time Survey/BSMAS (ABCD Study, 2021; Andreassen et al., 2017)

1. Do you have at least one social media account?
    a. *Yes/No*
2. Which social media site do you use the most?
    a. *Facebook*
    b. *Instagram*
    c. *Snapchat*
    d. *Twitter*
    e. *Watch or stream videos or live stream (such as YouTube, Twitch)?*
    f. *YouTube*
    g. *Pinterest*
    h. *Tumblr*
    i. *Reddit*
    j. *Multiplayer Videogame Online Chatting*
    k. *TikTok*
    l. *Other*
3. On (screentime_smq_use_most), is your account public or private?
    a. *-1=Not Applicable; 1=Public; 2=Private; 999=Don't Know; 777=Refuse to Answer*
4. Do you have a social media account that you keep secret from your parents?
    a. *1=Yes; 0=No; 777=Refuse to Answer*
5. On a typical week/weekend day, how many hours do you:
    a. Years 1 and 2: Visit social networking sites like Facebook, Twitter, Instagram, etc.? *0 = None; .25 = < 30 minutes; 0.5 = 30 minutes; 1 = 1 hour; 2 = 2 hours; 3 = 3 hours; 4 = 4+ hours //Example: 1½ hours would be coded as 1 hour, rather than 2 hours.*
    b. Years 3 and 4: Visit social media apps (e.g., Snapchat, Facebook, Twitter, Instagram, TikTok, etc.? (Do not include time spent editing photos or videos to post on social media.) *0=0; 1=1; 2=2; 3=3; 4=4; 5=5; 6=6; 7=7; 8=8; 9=9;*

10=10; 11=11; 12=12; 13=13; 14=14; 15=15; 16=16; 17=17; 18=18; 19=19; 20=20; 21=21; 22=22; 23=23

1=Never; 2=Very rarely; 3=Rarely; 4=Sometimes; 5=Often; 6=Very often; 777=Refuse to answer

6. I spend a lot of time thinking about social media apps or planning my use of social media apps.
7. I feel the need to use social media apps more and more.
8. I use social media apps so I can forget about my problems.
9. I've tried to use my social media apps less but I can't.
10. I've become stressed or upset if I am not allowed to use my social media apps.
11. I use social media apps so much that it has had a bad effect on my schoolwork or job.

Appendix F: Family Environment Scale–Family Conflict Subscale (Moos & Moos, 1994; Stover et al., 2010)

True/False

1. We fight a lot in our family.
2. Family members rarely become openly angry.
3. Family members sometimes get so angry they throw things.
4. Family members hardly ever lose their tempers.
5. Family members often criticize each other.
6. Family members sometimes hit each other.
7. If there's a disagreement in our family, we try hard to smooth things over and keep the peace.
8. Family members often try to one-up or outdo each other.
9. In our family, we believe you don't ever get anywhere by raising your voice.

Appendix G: Prosocial Behavior Survey (Goodman et al., 1998)

0 = Not True; 1 = Somewhat True; 2 = Certainly True

1. I try to be nice to other people. I care about their feelings.
2. I am helpful if someone is hurt, upset, or feeling sick.
3. I often offer to help others (parents, teachers, children).

Appendix H: Brief Problem Monitor (BPM; Achenbach et al., 2011)

0 = Not True; 1 = Somewhat True; 2 = Very True

Internalizing

1. I feel worthless or inferior. (Definition of inferior: less good)
2. I am too fearful or anxious.
3. I feel too guilty.
4. I am self-conscious or easily embarrassed.
5. I am unhappy, sad, or depressed.
6. I worry a lot.

Externalizing

1. I argue a lot.
2. I destroy things belonging to others.
3. I disobey my parents.
4. I disobey at school. (Interviewer: Please select "Not True" when participant is not in school at the time of the assessment.)
5. I have a hot temper.
6. I am stubborn.
7. I threaten to hurt people.