THE IMPACT OF SMARTPHONE USE AND SLEEP DURATION ON YOUTH MENTAL HEALTH

by

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Submitted in partial fulfilment of the requirements
for the degree of Master of Science

at

Dalhousie University
Halifax, Nova Scotia
July 2022

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

Previous research has consistently observed an association between smartphone use and poor mental health in youth, and how it displaces healthy habits such as sleep. However, many studies have only used subjective self-report measures, which can be problematic. Thus, additional objective assessments are needed and recent advances in mobile sensing technology offers the unique opportunity to quantify behaviour in a low-burden, unobtrusive manner. The present thesis sought to examine the associations between objectively measured sleep and smartphone use utilizing mobile sensing, and their impact on youth well-being, through two studies. The first study assessed the impact of objectively measured smartphone use on youth mental health, and the second study explored if sleep mediates the relationship between smartphone-based screen-time and mental health outcomes. The findings highlight the importance of sleep, underscore the detrimental effect of excessive smartphone use on youth mental health, and may inform future research and interventions.

LIST OF ABBREVIATIONS USED

ADHD	Attention-Deficit/ Hyperactivity Disorder
COVID-19	Coronavirus Disease 2019
PROSIT	Predicting Risk and Outcomes of Social Interactions
REDCap	Research Electronic Data Capture
SES	Socio-economic Status
SDQ	Strengths and Difficulties Questionnaire

ACKNOWLEDGEMENTS

I would like to express my gratitude to my supervisor, Dr. Sandra Meier, for her support and guidance throughout this degree. I could not have completed this project without her expertise and commitment to research. In addition, I would like to thank my committee members, Dr. Penny Corkum and Dr. Alexa Bagnell, for their time and thoughtful comments regarding this project. I would also like to extend my gratitude to the PROSIT team and to the individuals who have taken the time to participate in the study.

In addition, I would like to thank my husband for his support and patience, and my family for their encouragement. A special thank you for my mom – you are forever my inspiration.

CHAPTER 1. GENERAL INTRODUCTION

1.1 Smartphone use

Technology use has become ubiquitous, a trend enhanced by the use of mobile devices, such that 76% of people in countries with advanced economies and 45% of those in emerging nations own and use smartphones (Meyerhoff et al., 2021). People interact with digital devices and utilize the Internet for a wide variety of reasons: sometimes for education or social networking (Lee et al., 2020; Sung et al., 2016), other times for entertainment (Ophir et al., 2021; Sung et al., 2016), including for creative purposes (Sheldon & Bryant, 2016) or to document one's life and experiences (Orchard et al., 2014). Younger age seems to be highlighted as one of the most important predictors of frequency of use for various Internet services (Büchi et al., 2016), a tendency that is also reported in Canada, where youth have the highest use of smartphones across all age ranges: over 96% of them own a smartphone for personal use, and over 70% check their smartphone at least every 30 minutes (Government of Canada, 2021).

Worryingly, it appears that this access of smartphone use extends to younger and younger ages/age groups, such that some studies found that one in five preschoolers have access to smartphones and many of them can experience problematic use (Park & Park, 2021). Researchers have observed an increase in percentage of minors using smartphones and reporting problematic use (Fischer-Grote et al., 2019), and longitudinal studies (Madigan et al., 2019) suggest a directional association between duration of screen-time and poor performance in developmental screening tests among very young children. The observation of problematic smartphone use extends to adolescents and young adults studies pointing out a connection to risk taking behaviours, such as dangerous driving (Kuss et al., 2018), as well as an association between social networking apps and rumination in college students (Mao et al., 2022). Qualitative studies of problematic smartphone behaviour (Yang et al., 2019) have defined it as uncontrolled frequent checking of smartphone, overuse late at night, and irrelevant use of the device during important activities (such as during class). Along these lines, most undergraduates reported that their excessive use was driven in some cases by boredom, poor self-regulation, or a fear of missing messages, as such, youth are at particular risk of negative outcomes (Yang et al., 2019; Stiglic & Viner, 2019). Overall, it appears that smartphones are used at increasingly younger ages and in a maladaptive manner, to distract themselves from negative emotions, often with detrimental impact on their development and school performance.

1.2 Youth Well-being and Smartphone Use

Studies have underscored that smartphone use may be a significant factor leading to poor socioemotional outcomes, finding bidirectional associations between duration of screen-time and children's externalizing and internalizing behaviours (Neville et al., 2021); the results also emphasize that screen exposure has a complex and nonlinear association with psychopathology across childhood. For example, Eirich et al. (2022) found an association between duration of screen-time and both externalizing (i.e., aggression, attention deficit/hyperactivity symptoms) and internalizing (i.e., depression, anxiety) behaviors in young people. In addition, a large scale longitudinal cohort study of adolescents confirmed this observation, underscoring that there was a significant association between higher frequency of modern digital media use and subsequent ADHD symptoms over a 24 month period (Ra et al., 2018).

These findings are particularly concerning because decreases in the mental health of children and adolescents are associated with long-term physical health and chronic disease, along with detrimental effects on social relationships, education, and employment (Bitsko et al., 2022). Longitudinal studies of youth that exhibit externalizing and internalizing symptoms during childhood emphasize that they are more at risk to develop other types of psychopathologies through adolescence and young adulthood and that detrimental life outcomes impact not just families but their communities as well (Atherton et al., 2018; Neville et al., 2021).

A systematic review (Stiglic & Viner, 2019) found evidence that duration of screen-time was associated with poorer overall quality of life, decreases in self-esteem and well-being and poorer psychosocial health in children and young people. Moreover, there is increasing evidence that youth use their smartphones while engaging with other devices, such as using their phones while watching television to filter out unwanted content, such as advertisements (Stiglic & Viner, 2019), thus pointing that smartphones provide the majority of screen-time in young people.

A Canadian birth cohort study (McArthur et al., 2022) emphasized that duration of screen-time may account for negative socioemotional and developmental outcomes in children even above parenting style, and that youth from socially disadvantaged backgrounds are more at risks for internalizing and externalizing behaviours. This is concerning, because adolescents with problematic smartphone use come from lower socioeconomic-status environments, with lower levels of maternal education (Fırat et al., 2018), thus impacting young people that are already disadvantaged. Männikkö et al. (2020) confirms the observation that youth from low socioeconomic backgrounds may be more affected, and more worryingly, emphasize that the socioeconomic status (SES) of parents was associated with both physical inactivity and increased screen exposure in youth.

Literature overviews of mobile device use point to a multitude of negative psychosocial and physiological consequences (Lissak, 2018): besides poor sleep, excessive use can be a risk factor for high blood pressure, obesity, insulin resistance, as well as impaired vision and reduced bone density. On the mental health front, there has been observed an increase in depressive and ADHD symptoms, anxiety, insomnia, poor educational attainment and decreased prosocial behaviours (Lissak, 2018; Sohn et al., 2019). Screen media activity on multiple devices also appears to have an impact on brain characteristics and cognitive performance (Paulus et al., 2019), with some pointing to the addictive nature of mobile device use that can be linked to brain structural changes that affect emotional regulation and cognitive control (Lissak, 2018), which would explain some of the detrimental effects seen in psychosocial outcomes.

In particular, social networking apps appear to have a strong impact on youth well-being, and a variety of both cross-sectional and longitudinal studies emphasize the connection between smartphone and social media use in the increase in mental distress of youth that often leads to self-harm (Abi-Jaoude et al., 2020). A form of bullying greatly concerning in youth, that arose through social media communication (cybervictimization), appears to be a unique form of peer victimization, due to the technological particularities of this type of media that enable the broadcast of damaging information to a wider audience compared to traditional forms of peer victimization (Landoll et al., 2015). Furthermore, cybervictimization is associated with increased levels of depressive symptoms over time in adolescents and this effect appears to impact more adolescent girls, because they spend more time on smartphones engaged in social activity such as social media and texting, while adolescent boys prefer gaming (Twenge & Martin, 2020). Among both sexes, excessive users of social media were more likely over time to show increases in externalizing and internalizing symptoms, and to be low in well-being, have less self-esteem, and have increased risk factors for self-harm and suicide (Boers et al., 2019; Landoll et al., 2015; Twenge & Martin, 2020; Viner et al., 2019).

1.3 Intersectionality of Social Interactions with Active Screen-time

While more passive time spent on smartphone devices appears to be a deleterious due to its associations with poor mental well-being (Demirci et al., 2015; Sohn et al., 2019; Yang et al., 2019), not all forms of smartphone use appear to be detrimental. Keeping in mind that non-social features of smartphone use are most related to increases in depression and anxiety (Elhai et al., 2017) and that smartphone addiction is linked to loneliness in youth (Sönmez et al., 2021), it appears that social interactions on the device play an important role in more protective forms of screen-time (Boers et al., 2019).

A systematic review of the link between the use of social networks, depression, and anxiety (Seabrook et al., 2016) found differences between individuals' use and the network structure; for example, those that preferred to connect with strangers over familiar others during their use of apps, along with their motives of use, played a significant role in the varying levels of mental health issues reported. Some studies suggest young people utilize social media (such as Twitter, Facebook) for self-expression (Alhabash & McAlister, 2015; Seabrook et al., 2016) or to find sources of humor or a connection to others, which are protective for mental health (Hoge et al., 2017).

While social comparison has often been cited as a reason for increases in depression symptoms in youth (Seabrook et al., 2016), using social networking sites to maintain one's offline social network, or to widen one's social network by connecting with others outside of usual social circles, could help adolescents reduce the impact of detrimental uses on their mental well-being (Hoge et al., 2017; Orchard et al., 2014). Frequency of use of a social communication app (WeChat) was found by Pang (2022) to positively predict an individual's network size and diversity, along with increases in their social capital in real life and, consequently, improved satisfaction with life. Hou et al. (2017) highlighted that people who spend more time on online social networking also further develop their social skills, which they later apply in real life contexts.

The quality of these interactions appears to moderate these associations, such that positive quality interactions, increased social support, and feelings of social connectedness are related to lower levels of depression and anxiety (Seabrook et al., 2016). The benefits of access to social support were also emphasized by a meta-analysis of screen media as well (Ferguson et al., 2022). For example, the opportunity of remote social interaction may be uniquely beneficial to individuals with social anxiety who find face-to-face interaction difficult, and it may play an important role in supporting mental health of individuals with depression (Seabrook et al., 2016). Moreover, Canadian studies conducted during the COVID-19 pandemic found that connecting with others virtually during lockdowns was an effective way for adolescents to combat feelings of loneliness (Ellis et al., 2020; Parent et al., 2021).

While widening one's social network may offer the previously described benefits, it appears that many youth greatly benefit from using social media to maintain strong bonds with those familiar to them, such as close friends and family members: Paulich et al. (2021) observed that through increase in social media use, the quality of peer relationships appears to be positively impacted. The authors also found that more screen-time was associated with an increase in number of close friends, especially considering that adolescents are finding new ways to stay connected even when farther apart; for example, more and more online activities that use to be solitary (such as video gaming) are now social activities where young people play and interact with their peers (Paulich et al., 2021). Similarly, other studies have observed that youth frequently use social media (such as Snapchat) to bond with close friends and family members (Piwek & Joinson, 2016) and that the frequency of communication with others in the close support network through smartphones can be protective for youths' mental health (Moukaddam et al., 2019). Furthermore, it seems that frequent checking of the phone per day is associated with social communication with others, such as messaging or calls with family or friends, which can be protective of mental health (Beierle et al., 2020; Cao et al., 2020; Nagata et al., 2021; Shaw et al., 2020).

1.4 Impact of COVID-19 Pandemic

The COVID-19 pandemic has created unprecedented disruptions in the daily lives of both adults and young people, with detrimental effects on their mental health (Gallagher et al., 2020). Even before the pandemic the reports of problematic use of smartphones was linked to anxiety and depression in adults (Rho et al., 2019; Richardson et al., 2018) and in adolescents (Maras et al., 2015). The effects of the pandemic have only exacerbated this, with studies indicating poorer mental health trajectories for children and adolescents during this time period (Raw et al., 2021).

Concerningly, very young children (3 to 7 years old) appear to have engaged even more with screens during the pandemic than previously (Ribner et al., 2021); while most of the observed increases were for educational and entertainment purposes, children from low socioeconomic households appeared to be more at a disadvantage, having higher increases for non-educational purposes than those from higher socioeconomic backgrounds (Ribner et al., 2021). Worryingly, 85% of university students reported significative increases in smartphone use during pandemic restrictions, with 42% of them using their phones more than 6 hours per day, with some variances due to parental education, household income and gender (Saadeh et al., 2021).

In Canada, a youth study (Li et al., 2021) showed that levels of screen-time increased significantly during the pandemic, above the 1-2 hours recommendation by the Canadian Paediatric Society and that this greater screen use was associated with higher levels of mental health symptoms in children and youth, even after accounting for previous mental health diagnoses.

Even after easing of restrictions, it appears that these elevated rates remained constant, as noted by a large cross-sectional diverse sample of adolescents (Nagata et al., 2021). The authors suggested that adolescents may use screens to manage negative feelings or withdraw from stressors and screen-time provides them with a form of social connection that might offer some relief, particularly during uncertain times such as the pandemic. Chen et al. (2021) emphasized that certain behaviours may protect youth from mental health distress, such as adequate sleep and regular exercise. However, a cross-sectional study of Canadian families during the COVID-19 pandemic, observed that restrictions lead to less healthy behaviours, reporting an increase in overall screen-time and, simultaneously, significant decreases in health promoting behaviours such as physical activity and sleep (Carroll et al., 2020).

Importantly, these observations may provide a valuable insight into how screen-time may impair mental well-being in youth. Displacement theory (Cooper, 1994) suggests that the increase in smartphone use may actually be displacing other healthy daily behaviour of youth, such as socialisation, learning time, or sleep (Ophir et al., 2021; Stiglic & Viner, 2019), which in turn, negatively impacts youth mental health. Cyberbullying can accelerate some of these detrimental effects (Viner et al., 2019).

1.5 Importance of Sleep

Smartphone use is becoming more prominent in the modern sleeping habits of young people, both at bedtime and at waketime: 75% of youth report that before going to sleep, the last thing they do is check their phone and it is also the first thing they check upon waking up (Government of Canada, 2021). Many children and adolescents sleep with their phone in close proximity, and awake to check it during the night, due to fear of missing out (Long et al., 2021), which is a strong predictor of problematic smartphone use (Elhai et al., 2020). Meta-analyses found evidence of correlations between sleep quality, quantity, and problematic smartphone use in youth (Mac Cárthaigh et al., 2020), such that night-time social media use (Woods & Scott, 2016) and overall smartphone use during the night (Demirci et al., 2015) is associated with increases in anxiety and depression among young people, along with behavioral problems and negative impacts on academic performance (Paulich et al., 2021).

Sufficient quantity and quality sleep is essential to the well-being of youth (Baddam et al., 2018; Tarokh et al., 2016) and the relationships between sleep, behaviour, and mental disorders during early development are complex and often bidirectional (Alfano & Gamble, 2009; Baddam et al., 2018). The literature often points to the fact that insufficient or disrupted sleep may affect a young person's emotional regulation, which leads to behavioural issues and mental distress, and, at the same time, the psychiatric disorders of children and adolescents may exacerbate sleep problems in a cyclical manner (Alfano & Gamble, 2009). Psychiatric disorders cause disruptions in sleep: for example, over 80% of depressed patients complain of difficulties in falling or remaining asleep, and the magnitude of sleep issues increases with disease severity (Tarokh et al., 2014). Since many psychiatric disorders have their onset during adolescence (Paus et al., 2008), the importance of adequate sleep becomes particularly salient. These sleep issues also appear to persist in time (Alfano & Gamble, 2009), impairing a young person’s functioning into adulthood. Thus, it important that we identify and address early factors that impact sleep in young people.

The mechanisms through which screen-time impacts sleep may be varied, but recent research has theorized that melatonin suppression due to light exposure late in the evening or at night impacts the circadian rhythm and alters sleep patterns in children and adolescents (Crowley et al., 2018) and these effects appear to be quite detrimental to bioregulatory systems and youth physiology, through a vicious cycle of sleep disruptions that lead to increased use of the phone the next night (Touitou et al., 2016) because they are more inclined to postpone their bedtime (Geng et al., 2021). In turn, these disruptions impact physical and mental well-being, being observed effects on working memory, mood, cognitive performance and impulse control, and wide-ranging effects from substance use, motor vehicle accidents, mental health issues and behavioural challenges to eye strain, weight gain and weakened immune systems (Crowley et al., 2018; Sun et al., 2019; Xie et al., 2018).

In addition to the impact of light at nighttime, smartphone use can impact sleep through the effects of social media and social comparison or cybervictimization (as described previously in subsection 1.2), as well as through incoming notifications that disrupt sleep and negatively affect its quality (Godsell & White, 2019). Moreover, a longitudinal study (Vernon et al., 2018) found that young people using their phone at night engage in poor sleep behaviours that predict future declines in well-being, through increases in depressed mood and externalizing behaviours, along with decreases in self-esteem and coping ability. Their findings suggest that a change in sleep behavior, over and above usual adolescent fluctuations in bedtime behaviours, links increased night-time mobile phone use to declines in a range of well-being indicators. These observations were corroborated by research linking problematic smartphone use to addictive or compulsive behaviours (Boumosleh & Jaalouk, 2017), showing effects such as tolerance (increase in overuse over time) and withdrawal symptoms. Elhai et al. (2019) confirmed these results, finding that younger users with excessive smartphone use during the day that preferred entertainment activities, had markers of daytime tiredness, leading to late-night use that decreased their quality and quantity of sleep and increased their depression and anxiety.

A systematic review of reviews (Stiglic & Viner, 2019) found that due to the impact of blue screen light on sleep patterns that can affect attention and concentration, screen-time may cause delay of sleep onset, reduced total sleep time and daytime tiredness, among other poor sleep outcomes. Of those adolescents that reported insufficient sleep, many pointed to the influence of peers or distractions caused by electronic devices (Godsell & White, 2019); this behaviour appeared to be differentiated by gender, such that girls reported more communication activities on their mobile phones, while boys reported excessive video watching on their devices. In contrast, longer sleep duration appears to mitigate some of the detrimental effects, such as social difficulties and increased aggressive behaviours, as underscored by a large US cohort study that included 11,875 children with problematic behaviours (Guerrero et al., 2019).

1.5.1 Impact of COVID-19 Pandemic on Youth Sleep

The COVID-19 pandemic has also caused disruptions in lifestyle with negative consequences on sleep and mental health (Giuntella et al., 2021). Sleep duration appears to have decreased even in preschoolers, alongside an increase in screen exposure, leading to behavioural problems (Kahn et al., 2021). A large US study of adolescent sleep during the pandemic (Meltzer et al., 2021) observed variability in sleep patterns following the switch to online education, while large-scale surveys of students found multiple sleep problems, such as difficultly in initiating and maintaining sleep, insomnia and daytime functioning impairment (Zhang et al., 2021).

Youth suffering from mental distress may be more at risk of negative outcomes due to change and uncertainty, as caused by pandemic events. However, they may also experience some benefits as well (Becker & Gregory, 2020): having greater flexibility in their schedule (related to educational and social activities) may help to diminish "social jetlag", a discrepancy between weekday and weekend sleep patterns (Crowley et al., 2018). Moreover, youth who experience bullying or other school-related stressors may experience lower rumination around bedtime, or feel more secure around family members, which can positively impact sleep onset and quality (Becker & Gregory, 2020).

1.5.2 Assessing Sleep using Smartphones

Polysomnography, an in-lab sleep study method, is considered the gold standard in measuring sleep across various ages (de Feijter et al., 2022; Rundo & Downey, 2019). However, since polysomnography is very resource-intensive and restricts participant behaviour, other approaches have been devised to provide a more naturalistic recording of sleep in the patient's environment, such as wrist-worn actigraph devices. Actigraphy has been validated through comparison with polysomnography as a non-invasive objective tool for the study of sleep-wake rhythms (Yavuz-Kodat et al., 2019) and it has significant advantages, such as being less expensive and a more portable way estimating various facets of sleep behaviour, such as sleep duration, interruptions, sleep onset latency, etc. (Martin & Hakim, 2011; Haghayegh et al., 2019). Moreover, it is frequently used to assess sleep problems in participants that find polysomnography difficult, such as children with neurodevelopmental disorders (Yavuz-Kodat et al., 2019), and, in addition, it is often used to validate other activity monitors utilized in research studies (Kubala et al., 2020). However, actigraph devices are usually worn on the non-dominant hand and often use complex algorithms that may provide some methodological challenges (Berger et al., 2008), which is why it is often accompanied by sleep diaries and clinical interviews.

Due to the above advantages, actigraphy is commonly used to capture sleep in research studies (Brown et al., 2018); however, it appears that modern digital behaviours may interfere with its ability to accurately measure wakeful periods in individuals that engage with mobile devices at bedtime (Borger et al., 2019), since these users often experience a reduction in physical activity and movements, while being cognitively engaged. Thus, Borger et al. (2019) posit that touchscreen interactions might be an appropriate alternative to assess their behaviour and would be particularly salient for modern sleep, where smartphones are integrated both at sleep onset and waking up. Similarly, Ciman & Wac (2019) confirmed that an individual's sleep duration, start, and wake-up times, can be estimated with a small margin of error using the smartphone on/off patterns, similar to other wrist-worn devices, in an effective and resource-optimized manner.

1.6 Mobile Sensing Technology

A current limitation in the assessment of smartphone use behaviours and their impact on mental health is that most studies employ self-report data, which can be subjective and biased (Meyerhoff et al., 2021). For example, passive sensing studies that compared objective smartphone use with self-reports found that youth often underestimate the amount of time spent on the device and that parents are also subject to similar misestimations, with some under-reporting and some over-estimating how much their child uses their smartphone (Wade et al., 2021).

Given the ubiquity in access to smartphones, researchers can take advantage of this development and acquire more objective data through the use of these devices, with reduced participant effort and more overall value (Meyerhoff et al., 2021; Shaw et al., 2020). Their convenience and ease of use can enable researchers to reach participants that might otherwise not engage in studies, due to location or other constraints (Ferreira et al., 2016). Furthermore, they offer an unprecedented opportunity to collect a variety of real-life data that is generated through normal use, while placing a low burden on participants and patients, enabling the development of more effective, in-time, scalable interventions (Lind et al., 2018). Machine learning algorithms can further this technology, by identifying and predicting risks that would not be noticed through previous analysis methods, because such apps capture a variety of behaviours that can augment monitoring or match individuals with effective mental health treatments in a timely manner through objective measurement of psychiatric symptoms (Lind et al., 2018; Nickels et al., 2021).

Phone use patterns have been suggested to be able to capture the various social and behavioural manifestation of mental illness in naturalistic settings, in an unprecedented moment-by-moment quantification of disease phenotypes, presenting many opportunities for advancing research and augmenting clinical decision-making (Torous et al., 2016). Moreover, data collection through smartphones in clinical populations appears feasible even in longitudinal studies and it is consistently correlated with other approaches to data collections in patient groups (Matcham et al., 2022).

1.6.1 The PROSIT App

PROSIT (Predicting Risk and Outcomes of Social Interactions), the smartphone app used in the two studies included in the present thesis, has been developed by the PROSIT lab, at Dalhousie University (MacLeod et al., 2021), and encompasses passive sensing technology that collects a variety of data through the sensors integrated in the device in an unobtrusive manner. It was designed to have a youth friendly interface, being developed for both iOS and Android operating systems. PROSIT collects naturalistic data on how frequently and for how long a user interacts with the smartphone, as well as location, accelerometer (a tool to measure device movement), connectivity (to what other devices it is connected), call activity (duration, date and time, incoming or outgoing), ambient noise and light. The app initially stores data locally, and then uploads it regularly to a secure server when the phone is not in use, ensuring that it does not interfere with usual device use. Personal sensitive data, such as names, phone numbers, GPS location are anonymized through cryptographic hash functions (mathematical encryption algorithms used to secure and protect data). Figure 1 provides examples of app interface screens. A study by MacLeod et al. (2021) showed that passive collection of smartphone data (as described above) using the PROSIT app can successfully predict mental health distress, and provided evidence of high acceptability of this type of data collection, such that even youth with severe clinical symptomology reported only minimal issues in the use of the app.

1.7 Aims

Taking into account the theoretical considerations detailed previously, the two studies included in the present thesis aimed to advance the scientific knowledge related to the impact of smartphone use on youth mental health, utilizing innovative mobile sensing technology. To that end, the first study examined the differential impact of active and passive forms of smartphone use on mental health outcomes. Correspondingly, the second study aimed to investigate whether objectively measured sleep would mediate the association between smartphone-based screen-time and well-being in youth.

CHAPTER 2. THE IMPACT OF ACTIVE AND PASSIVE SMARTPHONE USE ON YOUTH MENTAL HEALTH OUTCOMES DURING THE COVID-19 PANDEMIC

Contribution Statement

The first study included in this thesis appears in this chapter. Silvia Marin-Dragu completed the data analysis and drafted the manuscript under the supervision of her research advisor, Dr. Sandra Meier. The manuscript was revised following feedback from her supervisory committee, composed of Dr. Penny Corkum and Dr. Alexa Bagnell. The data was collected by the PROSIT team.

2.1 Introduction

Presently, individuals use technology and Internet services for a variety of reasons, sometimes for convenience of accessing information, often for social interaction and entertainment (Erz et al., 2018; Fullwood et al., 2015; Sung et al., 2016). Age appears to be the most important predictor of frequency of use for various Internet services (Büchi et al., 2016), with young people (adolescents and young adults) being the most intensive users of this type of technology, spending an increasing amount of time, over the years, online each day (Boumosleh & Jaalouk, 2017; Rho et al., 2019). Previous research (Lee et al., 2020) has highlighted that youth frequently prefer to use their smartphone to access the Internet, due to its portability and ease of connectivity, compared to other available devices.

At the same time with the increase in smartphone use (Government of Canada, 2019), and the larger role these devices play in the daily lives of present youth, there has been growing concern regarding the impact of all types of screen-time on mental health (Elhai et al., 2017; Kuss et al., 2018; Yang et al., 2019). Recent studies on problematic mobile device use emphasize that youth may use their smartphone in a dysfunctional manner, due to fear of missing out or as a way to cope with adverse emotions (Elhai et al., 2020; Twenge & Martin, 2020), with some studies linking problematic use with addictive behaviours (S. Liu et al., 2019). Moreover, in children, longitudinal studies suggest that digital screen-time may be a significant factor leading to internalizing symptoms and other poor socioemotional and developmental outcomes (McArthur et al., 2022; Neville et al., 2021). Even before the COVID-19 pandemic, researchers raised concerns that screen-time may be a risk factor or marker of anxiety and depression in adolescents (Maras et al., 2015). The pandemic has only exacerbated this, triggering an increase in screen-time among both adults and children (Carroll et al., 2020; Chen et al., 2021). For example, a Canadian longitudinal cohort study investigating screen use and mental health symptoms during the pandemic found that youth with an increase in screen use had higher levels of mental health symptoms; younger children (2 to 4 year olds) were more predisposed to conduct problems, hyperactivity and inattention, while older children (mean age 11 years old) had higher levels of depression, anxiety and irritability (Li et al., 2021).

Given the existing evidence, there are strong reasons to expect an effect of smartphone use on mental health of youth. However, many studies have only used subjective self-report measures, which can be problematic due to recall biases and misestimation of actual time spent on the device (Wade et al., 2021). As such, more objective assessments are needed, to better understand the impact of smartphone use on youth mental health. Recent advances in mobile sensing technology may offer the unique opportunity to collect objective information continuously, in an unobtrusive manner (Ferreira et al., 2016; Torous et al., 2016). This type of technology can take advantage of the multitude of integrated sensors, often with minimal input from users, to passively record and quantify behaviour (Matcham et al., 2022).

Moreover, the various types of smartphone use could reflect the different motivations of youth and may be used as specific indicators of mental health outcomes. For example, previous research suggests that, in general, more time spent passively on the device is linked to worse mental health (Demirci et al., 2015; Sohn et al., 2019), and appears to be a deleterious type of smartphone use. On the other hand, frequent active checking of the device (phone pickups, number of unlocks) is associated with specific social activities, such as frequent messaging with friends and family, which can be protective of mental health (Shaw et al., 2020). Conversely, fewer social interactions and less device use to call or message friends and family, have been found to be predictive of higher depression symptoms among youth patients(Cao et al., 2020). Accordingly, frequent checking of the phone associated with frequent interactions with close friends and family can be considered an "active" type of smartphone use.

In conclusion, previous research provides supportive evidence for an association between smartphone use and youth mental health, however, many studies have only used subjective assessments that can be problematic and unreliable. Thus, we aimed to assess the impact of objectively measured smartphone use on youth mental health through a large-scale study. We utilized a mobile sensing app to collect objective data on smartphone use behaviour and explored its impact on mental health outcomes during the COVID-19 pandemic. Taking the current literature into consideration, we theorized that the type of device use measured will have a differential impact on youth's mental health. Consequently, we hypothesized that: (H1) an increase in duration of smartphone-based screen-time will be associated with worse mental health outcomes, while (H2) an increase in smartphone unlocks likely reflecting youth's social activities will be associated with better mental health outcomes. Finally, we hypothesized that (H3) there is a significant interaction between these two types of smartphone use, such that for youth with a high duration of screen-time, the effect of number of unlocks on mental health outcomes might be protective. The present study aimed to advance scientific knowledge through gaining a better understanding of the various ways in which objectively assessed smartphone use can impact mental health, which in turn, may help researchers and clinicians develop and optimize interventions and policies aimed at youth, parents, and educators.

2.2 Methods

2.2.1 Sample

We invited 550 English-speaking youth to participate, between June 2020-November 2021, aged 15-25 years old, with and without a mental health disorder, who had a smartphone with an iOS or Android operating system. We excluded participants who were inpatients at the time of recruitment because inpatients might often experience involuntary restrictions in accessing to their smartphones. To comply with existing COVID-19 policies, participants were recruited using ads on established online platforms and all contact with participants was made remote, through email or over the phone. The online platforms included social media (Facebook, Instagram), university electronic platforms (SONA) and popular Canadian ad sites such as Kijiji.

2.2.2 Procedure and Consent

Potential participants were guided through detailed information regarding study procedures and consent via "REDCap", a platform specifically designed to conduct online studies (Garcia & Abrahão, 2021) and approved by local health authorities. To ensure generalizability, both participants with and without a mental health disorder were included in the study. Youth were able to participate without parental/guardian consent but were given the option to inform their parents or guardians if they chose to do so. Through the online platform, participants were informed about the study, had the possibility to ask questions, and finally consented to participate in the study. The also provided demographic information and completed clinical questionnaires online using the secure REDCap platform. After completing the questionnaires, participants received instructions to download the mobile sending app (PROSIT) and use it continuously for at least 14 days.

The procedures of the study were approved by the research ethics board at Dalhousie University and abide the Declaration of Helsinki regarding ethical principles involving human participants. For their invested time, participants were compensated with a $60 CAD gift card.

2.2.3 Assessments

Mobile Sensing Technology

Mobile sensing technologies offer unprecedented opportunities to gain insight into youths' daily behaviour, by passively recording various types of data via the built-in sensors of smartphones from which objective information on youths' behaviour can be easily derived (Ferreira et al., 2016; Lind et al., 2018; Torous et al., 2016). The app used in this study (PROSIT), developed by the PROSIT lab (MacLeod et al., 2021a) is a passive mobile sensing app that unobtrusively collects information about smartphone use and can be easily used by youth. The app is available for both Android and iOS operating systems and has a simple, user-friendly interface; it collects data on smartphone interactions, accelerometer, location, screen-time activity, ambient noise and light, connectivity, and so on. All study participants were informed in detail about the data to be gathered by the app and could stop data collection at any timepoint. Collected data was uploaded automatically in the background to secure servers at Dalhousie University using state-of-the-art encrypted SSL connections. The app does not interfere with usual device use, thus likely providing valuable and accurate data. Although the app collects data from various sensors, for the purpose of the present study, we only focused on two types of smartphone use: screen-time (the duration the device was in use) and number of unlocks calculated based on the measured smartphone interactions.

Smartphone Use

Objective daily duration of screen-time can be calculated by summing up screen-time time periods – the time window in which a participant is actively using the phone, between turning on the display and turning off the screen. The operating system logs screen-time and with appropriate permissions by the user, and the mobile sensing app can access these logs and store them in a secure database. To assess changes in phone use, we also calculated the daily number of unlocks and total time spent using the smartphone across all screen-time activity windows. This methodology is in accordance with previous research in this area (Wade et al., 2021), which highlights that passive, objective sensing more accurately reflects the daily smartphone use behaviour of youth compared to self-report measures.

The Strengths and Difficulties Questionnaire (SDQ)

Mental health outcomes were assessed using the Strengths and Difficulties Questionnaire (SDQ). The SDQ (Goodman, 1997) is a widely used measure of psychological well-being in youth and has high concurrent validity with other common measures of mental health (Goodman & Scott, 1999). The SDQ includes 25 items on a 3-point Likert scale. For the purpose of the present study, two main factors were assessed as mental health outcomes: internalizing and externalizing symptomatology. The scale has good internal consistency (α =.73) and test-retest reliability (.62) (Goodman, 2001).

Self-reports of Screen-time Activity

In order to explore how the objective smartphone use data collected using mobile sensing was related to self-reports of screen-time, we also collected information about the daily habits of participants through an adapted questionnaire, similar to others used in research studies investigating youth screen-time activity during the COVID-19 pandemic

(Dickel, 2021; Raw et al., 2021). The questionnaire asked participants about how much time they spent on social activities with friends or family: calling, texting, video-calling, gaming, or communicating via social media; moreover, the participants were asked about how much time they spent playing video or app games, watching television/ Netflix/YouTube, listening to music, browsing the internet and posting content online/blogging. The following are examples of such questions: "During the past week, how much time per day did you spend talking on the phone?", "During the past week, how much time per day did you spend browsing the Internet?". The questionnaire included 6 answer options: "a) Did not do this activity, b) less than 30 minutes, c) between 30 minutes and 2 hours, d) 3 to 5 hours, e) over 6 hours, and g) Prefer not to answer".

Covariates

We collected demographic information such as age, sex, gender, socio-economic status, ethnicity, mental health diagnosis and treatment as well as education of parents through a self-report questionnaire adapted from a recent Statistics Canada Survey. Biological sex was included as a covariate in the analysis due to the literature pointing to different patterns of smartphone use (Godsell & White, 2019; Saadeh et al., 2021; Twenge & Martin, 2020), along with differences in prevalence of internalizing and externalizing symptoms in males and females (Atherton et al., 2018; Yong et al., 2014). Due to differences in the availability of sensors and how they collect data, we have included phone operating system type (iOS or Android) as a covariate, in order to rule out any potential confounding effects. As we included both participants with and without a mental health disorder in the study, we further included a current mental health diagnosis as a covariate. Finally, maternal education can have a significant impact on youth mental health

(Hosokawa & Katsura, 2017), and we also utilized maternal educational history as a proxy for socio-economic status (Jackson et al., 2017), since children may not estimate correctly family income, which is another factor that can increase the risk for poor mental health outcomes in youth (Bitsko et al., 2022).

2.2.4 Data Analysis

All statistical analyses were performed using the R programming language (version 4.1.2) and RStudio (version 2021.09.0/B351). From the initial 550 sample, 20 participants declined to participate. During quality control preprocessing, 10 participants with time windows that seemed to be caused by device misuse or technical errors, such as any period of screen time longer than 10 hours, were excluded from further analysis. Furthermore, 69 other participants had less than 14 days of app data collected and as such they were also excluded. Out of the remaining 451 participants, 28 (6%) had missing values on the internalizing symptoms factor of the SDQ, and 19 (4%) had missing values on the externalizing symptoms factor. These missing values were due to participants choice to select the "prefer not to answer" option to a question in the SDQ, so that no adequate symptom score could be obtained. Accordingly, those participants were excluded from further analysis.

First, descriptive statistics were computed for sample characteristics, predictors (screen-time and number of unlocks) and outcome variables (internalizing and externalizing symptoms). Next, we explored how objective mobile-sensed data is related to subjective self-reports of smartphone use by comparing these measures via Spearman correlations between mean duration of smartphone-based screen-time and number of unlocks and each of the self-reported screen activities described above. Correlation analyses were adjusted for multiple testing. To test our first two hypotheses, we ran a series of hierarchical multiple regressions to analyze the association between internalizing and externalizing symptoms (outcomes) and both types of smartphone use predictors (screen-time and number of unlocks), while controlling for the covariates described above: biological sex, phone type, mental health history and the education of the mother. Regression analyses were also adjusted for multiple testing. Finally, to test our third hypothesis, we ran linear regression models to assess of the interplay of these two types of smartphone use by including the interaction between duration of screen-time and number of unlocks. Specifically, we evaluated if adding the interaction improves the model fit and explains more variance in the outcomes of interest – internalizing and externalizing symptoms.

2.3 Results

2.3.1 Sample Characteristics

The sample (n=451) was predominantly female (83%), with an average age of 20.97 (SD = 2.49). For type of phone, 118 (26%) participants reported using a smartphone with an Android operating system and 333 (74%) had a phone with iOS, similarly to the phone types use rates reported by other Canadian studies (Brogly et al., 2021). Sample characteristics are further detailed in Table 2.1. A histogram depicting frequency of participants included in the analysis, by month of recruitment, is included in Figure 2. Participants used the app for an average of 30.63 days (SD=10.9), used their phone on average for 3.49 hours (SD = 1.79) and unlocked it 55.81 (SD= 35.13) times per day. The distributions of scores for internalizing and externalizing symptoms are depicted in Figures

3 and 4, respectively, and are similar to other studies conducted during the pandemic (Q. Liu et al., 2021; Ravens-Sieberer et al., 2022)

2.3.2 Objective and Subjective Screen-time Correlations

Spearman's rank correlation was computed to assess the relationship between mean duration of screen-time and number of unlocks. There was a moderate correlation between the two variables ($r(449)=.42$, $p < .001$). To compare objective smartphone use data collected using mobile sensing with self-reports of screen-time activity, Bonferroni adjusted Spearman correlations were calculated. All results are presented in Table 2.2 and significant results are highlighted below.

After corrections for multiple testing, mean screen-time per day was found to be significantly correlated with self-reported time spent browsing the Internet ($r(449)=.15$, $p =.02$), but none of the other self-reported screen activities (described in detail in the 2.2.3 Assessments section previously). In contrast, the average number of unlocks was significantly correlated with self-reported time spent texting with friends/family ($r(449)=.18$, $p=.001$) and communicating via social media ($r(449)=.18$, $p=.001$), but not the other self-reported screen activities.

2.3.3 Hierarchical Regression Models

To evaluate the two hypotheses evaluating the effect of passive overall screen-time and active effect of number of unlocks on mental health, we ran hierarchical multiple regression models to predict internalizing and externalizing symptoms as measured by the SDQ, using as predictors mean screen-time and number of unlocks and the covariates outlined previously. The results are presented in Tables 2.3 and 2.4 (Appendix).

At Step 1 of the analysis, we entered the four covariates (biological sex, phone type, mental health history and the education of the mother), and our results suggest that they account for 6.2% of the variance in externalizing symptoms and 9.4% of the variance in internalizing symptoms, respectively. Introducing the two smartphone use predictors in the models at the second step significantly improved the fit for both externalizing (R^2= .094, F(1,426) = 11.30, p <.001) and internalizing symptoms (R^2=.116, F(1,416) = 4.97, p <.001).

Our results revealed that mean duration of screen-time was significantly associated with externalizing (b=.19, t(425) =3.78, p < .002) and internalizing symptoms (b= .14, t(416) = 2.77, p =.012), in such a manner that an increase in duration of screen-time was associated with worse mental health outcomes. The results for number of unlocks were more diverse. The number of unlocks were significantly associated with internalizing symptoms (b= -.12, t(416) = -2.27, p =.048), in such a manner that an increase in unlocks was associated with less internalizing symptoms. In contrast, the association between the number of unlocks and externalizing symptoms was not significant (b=-.10, t(425) = -1.90, p =.12), however, it indicated a trend that an increase in unlocks might be associated with less externalizing symptoms.

2.3.4 Linear Regression Models Testing the Interaction

Our analyses revealed a significant interaction between screen-time and number of unlocks for externalizing symptoms (b=.11, t(424) = 2.27, p =.02), which improved the model fit (R^2= .094 compared to R^2= .105 , F(1,424) = 5.14, p = 0.02). In youth with a low mean duration of screen-time, the number of unlocks was positively associated with less externalizing symptoms, whereas in youth with high mean duration of screen-time the number of unlocks was associated with more pronounced externalizing symptoms. The model is presented in Table 2.5 and the interaction is shown in Figure 5. In contrast, no interaction was observed for internalizing symptoms ($F(1,415) = 0.72$, $p = 0.40$).

2.4 Discussion

The present study explored the association between objectively measured smartphone use, using a mobile sensing app, and youth mental health. We theorized that (H1) an increase in duration of smartphone-based screen-time will be associated with worse mental health outcomes for this population and (H2) the number of unlocks reflecting social activities will be associated with better mental health outcomes. We also hypothesized that (H3) there is a significant interaction between these two types of smartphone use. In addition, we also compared objective mobile sensed screen-time to subjective self-reports, to understand which screen activities the objective mobile sensing data is most likely to mirror.

We found that our results were, for the most part, supportive of the hypotheses and consistent with previous findings. The comparison between objective and subjective smartphone use revealed that mean duration of screen-time per day was correlated with time spent browsing the Internet (Cohen's d=0.3), which can be considered a more passive type of screen-time activity. Overall time spent on the smartphone has been suggested to be a more detrimental type of screen-time due to its association with worse youth mental health outcomes, such as increases in anxiety, depression and sleep issues (Demirci et al., 2015). Moreover, general duration of screen-time has been found problematic and has also been associated with stress and poor educational attainment in children and young people (Sohn et al., 2019). The results of the present study confirm these previous findings, by describing a significant association between average time spent on the device per day and both internalizing and externalizing symptoms in youth. One explanation for the relationship of screen-time with worse mental health outcomes may be provided through displacement theory (Cooper, 1994), suggesting that the deteriorating effect of high duration of screen-time on mental well-being may not be due to the smartphone use in and of itself, but rather due to it displacing other wellness-promoting activities for youth, such as quality sleep or physical activity (Liu et al., 2019). Sufficient sleep and physical activity are imperative for the development and mental well-being of young people, and excessive screen-time can disrupt daily routines by impacting circadian rhythms and causing daytime fatigue (Touitou et al., 2016), which leads to behavioural problems and poor academic achievement. In contrast, physical activity and adequate sleep can mitigate the negative effects caused by screen use and excessive social media on youth mental health (S. Liu et al., 2019; Stiglic & Viner, 2019).

However, not all types of smartphone interactions may be detrimental, and our results highlight this difference as well. The comparison between average number of unlocks and self-reports revealed an association with self-reported time spent communicating with friends and family using the smartphone, such as through social media and texting. The literature suggests that frequency of communication with others in the close support network through smartphones can be protective for youths' mental health (Moukaddam et al., 2019). Our results indicate that youth who lock and unlock their device frequently likely do so to fulfill their social needs, pointing to an active type of smartphone use. Specifically, an increase in unlocks was found to be significantly associated with less internalizing symptoms in youth and showed a trend with a decrease in externalizing symptoms as well.

Our analysis of the interplay between the two types of smartphone use observed a significant interaction between them for externalizing symptoms, but not for internalizing symptoms. These findings suggests that in youth with a high duration of screen-time, the number of unlocks was associated with more pronounced externalizing symptoms, while for youth with a lower duration of screen-time, the number of unlocks was associated with less externalizing symptoms. This finding underscores that overall time spent on the device is more passive and indicative of worse mental health outcomes. In contrast, in individuals with less overall time spent on the device, frequent interaction with the device (unlocks) may point to more active use and protective social behaviours.

Considering that smartphone use covers a wide variety of activities that youth engage in on their device, it may be needed to collect more fine-grained data on the types of uses and their impact on mental health. Moreover, youth may also alternate the duration and patterns of use depending on other activities they are engaged in, and some meta-analyses have observed a change in patterns of use between the weekdays and the weekend (Stiglic & Viner, 2019). Recent meta-analyses emphasize that there is still a debate on the impact of smartphone use on youth mental health (Ferguson et al., 2022; Ophir et al., 2021); thus, more research is needed on order to fully disentangle the passive and active behavioural patterns of youth in relation to smartphone use.

2.4.1 Strengths and Limitations

To our knowledge, the present study is one of the first to explore active and passive smartphone use and their impact on youth mental health using objective data. A strength of the current study was that it utilized an objective assessment of device use through the use of mobile sensing technology in combination with the usual self-report assessments. Recent research (Neville et al., 2021) has highlighted objective measurement of smartphone use as a significant methodological advancement for the field and the present study builds on this observation through continuous objective data collection that can provide a more accurate and data-rich source of behaviour monitoring compared to self-report measures. Studies employing passive sensing of smartphone behaviour in youth underline the potential measurement biases of self-reports. A recent study using a two-informant strategy indicated that youth themselves tend to under-report smartphone use (Wade et al., 2021), while their parents rather overestimated the smartphone activity of youth. Thus, relying solely on subjective reports of device use from youth or other reporters is likely misleading and resulting inaccurate assessments of behaviour, which can negatively impact studies that examine their effects on the well-being of youth. As such, more objective measures are needed, and passive sensing technology can be an unobtrusive way to measure youth daily behaviour more reliably.

The representativity of the sample may be considered a limiting factor, since it was self-selected, predominantly female and limited to English-speaking youth that owned a smartphone. Although women are more likely to participate in health research studies (Galea & Tracy, 2007), it is important for future research to ensure representativity through a more balanced recruitment. Additionally, adding other types of smartphone uses and diverse devices might help disentangle some of the results obtained, and may provide more specific information regarding how particular behaviours impact mental health outcomes.

2.4.2 Future Directions

Future research should consider recruiting a more representative sample, through more targeted and balanced techniques that will ensure generalizability of results. Moreover, it is important that future studies strive to disentangle active and passive forms of smartphone use and its impact on mental health outcomes through a more fine-grained monitoring of behaviour. For example, data could be collected on patterns of use, such as on the weekend and on weekdays. General screen-time information might not provide the level of detail necessary to capture specific daily behaviours; as such, it may be more informative to collect time spent on specific apps, in order to observe a differentiation in how the youth are using their phone, whether for productive purposes (such as education or work), entertainment, connecting with others socially or as a distraction (to manage negative feelings or withdraw from stressors) (Nagata et al., 2021). For example, a study exploring a messaging platform (WeChat) showed that some youth benefit from increased use of the app by diversifying and increasing their social network, which brought them higher life satisfaction (Pang, 2022). However, another study on that same messaging app (Mao et al., 2022) suggested that excessive use of the platform is linked to maladaptive cognitions and rumination in college students. Researchers also highlight that excessive use of one app may be reinforcing addictive behaviours for the use of other apps as well (such as WeChat and Weibo), with negative consequences for youth mental health and their social skills (Hou et al., 2017). Qualitative exploration of motives of use may be employed to explain why youth choose to use their device for particular activities and quantitative research can assess frequency of use and how these aspects impact their well-being.

2.4.3 Conclusions

In conclusion, the present study explored the associations between smartphone use and youth mental health through a multi-method approach. The current study addresses the lack of objective measurements of smartphone use in previous research by utilizing innovative mobile-sensing technology, in order to assess behaviour of youth in a more accurate manner compared to self-report measures. Importantly, the present study distinguished between active and passive types of smartphone use, highlighting the differentiated associations with internalizing and externalizing symptoms in this population. These findings may help inform youth, parents, clinicians, and educators: while not all forms of smartphone screen-time are detrimental, and social interactions on the device may provide some protective benefits, excessive smartphone use appears to have a deleterious impact on mental health. -. Given the lack of fine-grained behavioural and motivational observations of how youth interact with their devices, we conclude that more research in this area would be beneficial in order to better understand how mobile device use impacts youth mental well-being.

CHAPTER 3. IS THE RELATIONSHIP BETWEEN SMARTPHONE BASED SCREEN-TIME AND YOUTH MENTAL WELL-BEING MEDIATED BY SLEEP?

Contribution Statement

The second study included in this thesis appears in this chapter. Silvia Marin-Dragu completed the data analysis and drafted the manuscript under the supervision of her research advisor, Dr. Sandra Meier. The manuscript was revised following feedback from her supervisory committee, composed of Dr. Penny Corkum and Dr. Alexa Bagnell. The data was collected by the PROSIT team.

3.1 Introduction

Adequate sleep is a core component of mental well-being, and it is vital for adolescent and young adult brain function and behaviour (Seabrook et al., 2016). Sleep is essential for brain development, learning, memory, and emotion regulation. Deficits in sleep and disruptions in daily rhythms are further linked to a range of indicators of poor mental health (Tarokh et al., 2016). Sleep issues have complex relationships with psychiatric disorders for children and adolescents (Alfano & Gamble, 2009). On one hand, disturbed and insufficient sleep may interfere with a youth's ability to regulate their emotion and behavior, which impacts their functioning across numerous areas and is associated with mental health problems (Alfano & Gamble, 2009; Baddam et al., 2018). On the other hand, childhood psychiatric disorders may exacerbate sleep problems (Tarokh et al., 2014). Thus, it is imperative that we have a good understanding of what can impact youth sleep in order to optimize well-being for this population.

Recent research has been highlighting a growing concern regarding the impact of screen-time use late in the evening and at night on youth mental health (Godsell & White, 2019; Woods & Scott, 2016). It is common for adolescents and young adults to sleep in close proximity to their smartphones (Tarokh et al., 2016) and for over 72% of Canadian youth, the last thing they check before going to sleep is their smartphone (Government of Canada, 2021). The strong influence of smartphone use on the daily habits of youth is underscored by the fact that Canadian youth have the highest rate of smartphone ownership compared to all other age groups and over 97% have access to at least one smartphone (Government of Canada, 2021), which is a similar rate to other developed countries across the globe (Lee et al., 2020). On its own, smartphone use has been linked to worse mental health outcomes in youth (Elhai et al., 2020; Yang et al., 2019). Some studies point to technology use as substituting in-person social interaction and learning emotion regulation skills, which may be linked to anxiety and depression in youth (Hoge et al., 2017), while others suggest that associations between nighttime digital media use and poor sleep may lower self-esteem and increase levels of anxiety and depression in young people (Woods & Scott, 2016).

Smartphone use is theorized to impact youths' sleep in multiple ways. For instance, spending a long time on the smartphone late in the evening might lead to reduced sleep duration (Godsell & White, 2019), whilst incoming alerts during the night and fear of missing out on new content or messages could cause sleep disruptions (Elhai et al., 2020; Long et al., 2021). Furthermore, screen exposure before bedtime and the consequent adverse impact of this on melatonin production and the circadian rhythm are also possible mechanisms (Touitou et al., 2016). Finally, sleep quality and quantity could also be affected by levels of stress or worry from cyberbullying experiences and technology-based social comparison (Hoge et al., 2017; Landoll et al., 2015; Viner et al., 2019). Importantly, displacement theory (Cooper, 1994) implies that duration of smartphone-based screen-time may be substituting other wellness-promoting activities such as sleep, which in turn impacts youth mental health. For example, a study on smartphone overuse in university students (Boumosleh & Jaalouk, 2017) found that over a third of participants acknowledged decreased sleep quality and duration due to late-night smartphone use, with subsequent tiredness during the daytime. A similar study (Geng et al., 2021) reported that youth who use their smartphone in a problematic manner are more inclined to postpone their bedtime, leading to increased anxiety and depression. We thus hypothesize that smartphone-based duration of screen-time late in the evening/ at night will be associated with reduced sleep, resulting in poorer mental well-being.

The novel coronavirus disease (COVID-19), first diagnosed in December 2019, has severely impacted the daily life of both adults and children, negatively affecting their mental health (Gallagher et al., 2020). Many countries have implemented restrictions on social activities, and this has significantly impacted the daily lives of youth, often times transitioning educational activities to online platforms and restricting their ability to interact and socialize with peers or persons outside their immediate family. Disruptions in physical activity, sleep, mental health and increases in screen-time have been documented (Giuntella et al., 2021). Researchers have theorized that the pandemic response can have a varying impact on the sleep habits of youth (Becker & Gregory, 2020): on one hand, less exposure to the outdoors, more sedentary time, increased quantity of exposure to technology and the Internet may negatively affect sleep routines for youth. On the other hand, some youth may experience improved sleep, due to less time spent commuting to school or other extracurricular activities, as well as avoiding early morning start times, enabling them to have more time to sleep. Being removed from situations of peer victimization and other school stressors, while participating in more family bonding activities may also create feelings of safety that reduce rumination around bedtime and promote healthy sleep (Becker & Gregory, 2020; Boers et al., 2019; Godsell & White, 2019). As such, we theorize that while smartphone use will be increased during the COVID-19 pandemic overall (Chen et al., 2021) for youth, those with higher rates of smartphone screen-time late at night and altered sleep patterns will have worse mental health outcomes, in a similar manner as before the pandemic, but more pronounced.

The literature draws attention to the fact that timely objective assessment of behaviour in mental health studies is currently lacking and that smartphone sensors could provide a low-cost, unobtrusive way to capture real-world data (Meyerhoff et al., 2021; Torous et al., 2016). Considering that previous research has mostly utilized subjective self-report, which can be affected by recall biases, the findings may not fully reflect the context and variability of youth behaviour. Moreover, youth often misestimate their duration of screen-time (Wade et al., 2021) and studies have shown that passively recording information through smartphone sensors, with minimal input from users, is a low-burden way of assessing behaviour as accurately as other methods of data collection (Matcham et al., 2022). Thus, the present study aims to advance current research on smartphone use and its effect on mental well-being by objectively and continuously recording youths' smartphones screen-time via a mobile sensing app. Furthermore, a mobile sensing app can also objectively quantify sleep behaviour in users because touchscreen interactions are widely integrated into modern sleeping habits, both at the onset and at waking-up (Geng et al., 2021; Government of Canada, 2021). While historically sleep has been quantified by studies through measures such as sleep diaries and actigraphy, recent research (Borger et al., 2019) suggests that these methods may not estimate sleep correctly. Sleep diaries are subject to self-report limitations and many smartphone users have periods of intense cognitive activity interacting with the smartphone in bed before and after sleep, along with a reduction in body movements, which would lead to overestimation of sleep by actigraphy. However, a passive measurement of smartphone use may be a more accurate measure of wakefulness in youth compared to measures of body movements, thereby addressing a limitation in the current research.

In conclusion, previous research points to associations between increases in duration of smartphone-based screen-time, reduced sleep and poor youth mental health, however, the use of subjective assessments may be problematic and not fully reflect the variability of real-life data. As such, we aimed to investigate the effects on youth mental well-being through the use of objectively assessed sleep and duration of smartphone-based screen-time. For this purpose, we collected the data passively, using mobile sensing technology; given the context described previously, we theorized that: (H1) an increase in objectively measured duration of smartphone based screen-time would be associated with a worsening in youth mental well-being; and (H2) reduced sleep would mediate the associations of duration of screen-time and poor mental well-being.

3.2 Methods

3.2.1 Sample

Our initial sample consisted of 550 youth, with ages between 15 and 25 years old, who spoke fluent English and owned a smartphone (iOS or Android). The data was collected starting in June 2020 and ending in November 2021. Participants in inpatient treatment were excluded from the study. Taking into consideration COVID-19 restrictions, all contact was through remote means, such as emailing or calling. Potential participants were recruited through online methods, such as university electronic platforms (SONA), popular social media platforms (i.e., Instagram, Facebook) and established Canadian ad sites (i.e., Kijiji).

3.2.2 Procedure and Consent

All study procedures abide by the Declaration of Helsinki and were approved by the Dalhousie University Research Ethics Board. Participants received a $60 CAD gift card as compensation for their time. A platform specifically developed for research studies (REDCap) was utilized to guide potential participants through the study procedure and to provide their consent. Adhering to ethical principles, youth were able to participate without guardian consent, however, they had the option to inform their guardians if they wanted to do so. The online platform offered detailed information about the purpose and steps of the study and provided opportunities to request more information or ask questions. Participants provided their consent to participate in the study through REDCap. The same secure online platform collected demographic and clinical information through questionnaires. After completing this step, participants were provided with detailed instructions on how to install and download the mobile sensing app (PROSIT) and were recommended to use it for at least 14 consecutive days.

3.2.3 Measures

Objective Duration of Smartphone-based Screen-time

Data on objective duration of smartphone-based screen-time, in seconds, was collected through mobile sensing technology, because it offers the valuable opportunity to passively record information using the multitude of built-in sensors of the device. For the purpose of the present study we focused only on the amount of time the device was in use and we utilized the PROSIT app, previously described in detail elsewhere (MacLeod et al., 2021). The app is available for the most widely used operating systems (iOS and Android) and has a youth-friendly interface. Participants received detailed information regarding the data collected and all information was uploaded to secure databases at Dalhousie

University. Duration of screen-time was calculated by summing up the intervals between the time when the user turned on the device and actively used it and the time the screen was turned off. This passive, low-burden method of data collection reflects more accurately the behaviour of youth when compared to subjective self-report assessments, and is in accordance with similar research in this area (Wade et al., 2021).

Sleep

Sleep duration, in seconds, was retrospectively assessed for a time window of at least 14 days, during which we recorded data on smartphone activity. A sleep algorithm was created to identify the night-time intervals when the device was not in use, which would suggest a sleep episode, in line with similar previous research (Ciman & Wac, 2019). The sleep intervals had to be longer than 4 hours and less than 10 hours, between late evening (9pm) and early morning (9am). Due to recent research theorizing that youth may suffer from "social jetlag", a discrepancy between weekday and weekend sleep duration (Crowley et al., 2018), we also computed values for sleep times during the week and amount of sleep during the weekend; accordingly, we also calculated separate smartphone-based screen-time mean values for weekday and weekends, to investigate behaviours differentially by day of the week.

Youth Mental Well-being

The Strengths and Difficulties Questionnaire (SDQ) (Goodman, 1997) was used as a measure of youth mental well-being, due to its high concurrent validity with similar assessments of youth mental health (Goodman & Scott, 1999) and it has good internal consistency (α =.73) and test-retest reliability (.62) (Goodman, 2001). The questionnaire asks the participant to rate 25 affirmations on a three-point Likert scale and provides an assessment of two main factors – internalizing and externalizing symptoms.

Covariates

Demographic data was collected using an adapted Statistics Canada self-report questionnaire, and included information on age, biological sex, gender, ethnicity, mental health diagnosis, socio-economic status, and parental education. Taking into consideration differences influenced by sex in the prevalence of externalizing and internalizing symptoms (Atherton et al., 2018), as well as smartphone and sleep behaviour (Godsell & White, 2019), biological sex was considered a covariate. Mental health history (previously receiving a mental health diagnosis or treatment for a mental health disorder) was also included as a covariate in the analysis, due to the inclusion in the sample of both healthy participants and of those with a mental health disorder. Maternal education was considered a substitute for socio-economic status, and it was considered a covariate due to its significant impact on youth externalizing and internalizing symptomatology (Hosokawa & Katsura, 2017). Finally, phone operating system type (Android or iOS) was included as a covariate due to differences in how sensors collect data, to exclude any potential technical confounders.

3.2.4 Data Analysis

The R programming language (version 4.1.2) was used to conduct the analyses reported in the study. 550 participants were invited to the study and 20 individuals declined to participate. We excluded participants with values of smartphone screen-time that were considered extreme (over 10 hours per day), who had inconsistent technical data or who had less than 14 days of app data collected; overall, at this step, 79 participants were excluded from further analysis. 44 other participants did not have qualifying sleep data and were also excluded. From the remainder 407, some participants opted to not answer one item on the mental well-being questionnaire (SDQ), which precluded the calculation of a total score on the internalizing or externalizing factor. As such, we excluded from further analysis 26 participants with these missing values on internalizing and 18 on externalizing.

In the first step of the analysis, we calculated descriptive statistics for the sample. For our first hypothesis, we used hierarchical multiple regressions to analyze the association between duration of smartphone-based screen-time as predictor and the two SDQ factors as outcomes. To evaluate our second hypothesis, we conducted a mediation analysis that investigated whether sleep duration mediates the relationship between the predictor and outcome, using the "lavaan" package for structural equation modelling; analyses were performed using maximum likelihood estimates with bootstrap standard errors based on 500 samples (Rosseel, 2012). All analyses were controlled for the following covariates: type of phone, history of mental health, biological sex, mother's education.

3.3. Results

3.3.1 Sample Characteristics

Table 3.1 details the characteristics of the sample included in the analysis. It consisted of a total of 407 participants, with an average age was 20.94 years old (*SD*=2.5). 84% of the sample reported their biological sex as female (342 participants). 302 (74%) of the total participants owned an iOS device, while 105 (26%) used the Android operating system. For the study, the participants used the app for an average of 31.41 days (*SD*=11.01) and the mean duration of smartphone-based screen-time per day was approximately 3.57 hours (*SD*=1.71). The average duration of sleep per day recorded by the app was 7.44 hours (*SD*=0.99).

3.3.2 Hierarchical Regression Models

To test our first hypothesis, that investigated the associations between increases in objectively measured time spent using the smartphone and youth mental well-being, we ran two hierarchical regression models, one for each outcome variable (internalizing and externalizing factors of the SDQ). The results are detailed in Tables 3.2 and 3.3. At Step 1 of the analysis, we entered the four covariates described previously, and our results suggest that they account for 6.7% of the variance in externalizing symptoms and 9.6% of the variance in internalizing symptoms, respectively. Introducing duration of screen-time in the models at the second step significantly improved the fit for externalizing (R^2= .086, F(1,383) = 7.76, p <.001), and it indicated a trend for internalizing symptoms (R^2=.102, F(1,375) = 2.56, p =.11).

The results suggest that the average time spent on the smartphone was significantly associated with the externalizing symptoms factor (b=.14, t(383) =2.79, p = .006), such that an increase in duration of smartphone-based screen-time was linked to more externalizing symptoms. In contrast, the association with the internalizing factor was not significant (b=.08, t(375) =1.60, p = .11).

3.3.3 Mediation Analysis

We conducted mediation analyses to assess whether sleep mediated the relationship between mean duration of smartphone-based screen-time and internalizing symptoms, however, the direct (b=0.070, p >.05) and indirect paths (b=0.011, p >.05) were not significant.

We proceeded with the analysis to evaluate whether sleep mediates the relationship between smartphone screen-time and externalizing symptoms, while controlling for the covariates. The results of the mediating analysis are reported in Table 3.4. The results showed that the indirect effect was significant (b=0.042, $p < .01$), such that higher levels of screen-time are associated with reduced sleep duration and further associated with more externalizing symptoms. The direct effect was not significant (b=0.100, $p > .05$), suggesting that the effect is fully mediated. The model accounts for 10.5% of the variance in externalizing symptoms, which is a small effect size. The relationships are presented visually in Figure 6 using standardised coefficients.

Similar analyses (detailed in Tables 3.5 and 3.6) were performed to investigate the associations between amount of sleep during the weekdays and during the weekend, with the mean duration of weekday and weekend screen-time as predictor for each, and externalizing symptoms as the outcome variable. Average sleep during the weekdays was 7.42 hours (SD=1.07) and mean sleep during the weekend was 7.49 (SD=1.30). The results of the mediation analyses showed that the indirect effects of both average sleep during the weekdays (b=0.035, p <.05) and during the weekend (b=0.030, p <.05) were significant, while the direct effects were not significant (b=0.088, p >.05), respectively (b=0.111, p >.05), mirroring the implication of full mediation for these two mediators.

3.4 Discussion

Considering the growing concern regarding the impact between smartphone use and sleep on youth mental well-being, the current research sought to advance the understanding of these relationships in an objective manner. To fulfill this aim, data was collected on youth behaviours passively, using mobile sensing technology. We theorized that an increase in duration of smartphone-based screen-time would be linked to worse mental health outcomes and that sleep will mediate this relationship. We found that, for the most part, our results supported these hypotheses and were in line with previous similar research. In our sample, more screen-time was associated with increases in externalizing symptoms, but not internalizing symptomatology.

Some studies (Eirich et al., 2022; Kahn et al., 2021; Männikkö et al., 2020) have found associations between both internalizing and externalizing symptoms and increases in overall duration of screen-time on various devices, suggesting that this behaviour is linked to emotional dysregulation that causes distress in younger persons. A Canadian study showed longitudinal negative effects of parent reported screen-time on the development of young children (Madigan et al., 2019). However, as children enter preadolescence, the directionality of the association is not as clear, with some suggesting a bidirectional effect (Neville et al., 2021), such that some children that display externalizing problems might receive access to screens to manage the problematic behaviour.

Recent research (Paulich et al., 2021) investigating screen-time associations with early adolescent mental health found varying results, such that increases in screen-time duration were linked with both internalizing and externalizing problems in males, but only with externalizing problems in females. These relationships appeared to be influenced by social factors (such as number of close friends), which indicates that there are potential variables that might impact the association between screen-time and mental well-being in youth. To disentangle some of these effects, it is important that future research considers the diverse impact sex and gender might have on how the time is spent on smartphones and how social interactions (for example frequency of interacting with peers via the device) moderate mental health outcomes.

Given that studies (Lissak, 2018) link the adverse psychological effects of screen-time in children and adolescents to sleep, we examined its impact through a mediation model. Our results highlight that sleep significantly mediates the relationship between duration of smartphone-based screen-time and externalizing symptoms and underscore that reductions in sleep are quite detrimental for youth mental well-being. While some studies (Sun et al., 2019) observed some differences in the impact of weekday and weekend sleep on mental health outcomes, our mediation analyses did not reveal any discernable differences, which could be explained by the disruption in daily routines caused by pandemic restrictions (Becker & Gregory, 2020) . Further investigation in future studies of other sleep factors such as timing and night-time interruptions might reveal more complex interactions between externalizing and internalizing symptoms and day of the week differences.

A previous study conducted on Australian youth using questionnaires (Vernon et al., 2018) found that those who reported using the mobile phone during the night experienced increases in depressed mood and externalizing behaviour, along with decreases in self-esteem and coping. The present study confirms these previously detrimental observed effects through an objective measuring of sleep behaviour, highlighting the importance of night-time smartphone behaviour on youth development and well-being.

3.4.1 Strengths and Limitations

The current research is one of the first studies of its kind, to the best of our knowledge, that investigated the mediating potential of objectively measured sleep on objective measured duration of smartphone-based screen-time and youth mental well-being. This type of assessment is a strength, because it addresses the challenges posed by more subjective measures in studying the effects of mobile devices, such as self-report (Neville et al., 2021). It can also be considered an advancement, since it provides a low-burden method of quantifying behaviour, free of recall biases.

However, not all forms of device use have detrimental impacts and effects on youth. While excessive use is generally perceived as being problematic (Elhai et al., 2020; Yang et al., 2019), the pandemic has underscored that young people also use technology for positive purposes, such as education or entertainment (Ribner et al., 2021) and for social interaction with peers, family, and other persons important for them (Pang, 2022). Given that the present study only investigated average overall smartphone screen-time, this can be limiting in examining the various facets of mobile technology uses, both active and passive. A closer examination of both motives of use, as well as types of activities and apps engaged in on the device, might provide a more nuanced and varied understanding of real-life behaviour related to mobile devices.

Measuring sleep objectively, through smartphone interactions, might be viewed as a good still very new alternative to other technologies such as actigraphy (Borger et al., 2019), having the advantage of reaching a larger number of participants and assessing behaviour in a naturalistic manner. This type of assessment becomes more salient for younger participants, since many of them report using their phone in bed, awake, while engaging in very little physical movement (Vernon et al., 2018). However, it is a technology still in the early phases of development, compared to actigraphy, which has been researched and validated over a longer period of time. The algorithm employed in the present study may be considered too simplified in its current form, and this type of measurement can be improved by increasing the complexity of data being collected during the night-time. For example, collecting and analyzing data on sleep interruptions may provide valuable information. Tracking the quantity, as well as the reason for interruptions (such as a call, message or incoming social media notification) can better inform interventions and educational initiatives aimed at youth. Future research could also obtain more nuanced information by also investigating other sleep related components that have been observed as meaningful to youth mental well-being, such as sleep onset latency, sleep quality and daytime disfunction (Joshi, 2022). Moreover, corroborating sleep data with information from other device sensors (for example ambient light and sound) may provide a glimpse into the environmental context where the young person is resting.

Another limitation may be derived from the fact that the majority of the sample was female, and this aspect may impact the generalizability of results. While female participants are more likely to volunteer to participate in research (Galea & Tracy, 2007), we must take into consideration that girls and young women are more likely to experience psychological distress due to mobile device use, particularly through the detrimental effects of social media (Abi-Jaoude et al., 2020). As previously discussed, an investigation of mental health outcomes by gender through gaining a more fine-grained understanding of the differential time spent on various apps, might disentangle some of these effects. Finally, other types of mediators can account for some of the variances observed in mental health outcomes, and physical activity appears to be another important wellness behaviour impacted by excessive smartphone use (Carroll et al., 2020; Giuntella et al., 2021) and its impact should be considered in future studies.

3.4.2 Future Directions and Conclusions

To further advance these findings, studies may consider a mixed-methods approach, by collecting more finely grained data through both objective and subjective means. Mobile sensing technology can be employed as a resource-optimized way of quantifying youth behaviour both during the day and at night, and quantitative and qualitative surveys can provide insight into the reasoning for these behaviours. Taking advantage of the multitude sensors embedded in devices, richer contextual information can be gathered, such as environmental interferences at night or sleep onset and quality, to improve the complexity of the sleep algorithm. Moreover, other mediators such as physical activity and daytime tiredness could provide a more complete overview of factors impacting youth mental well-being. Furthermore, it is important to consider recruiting a more representative sample, as well as investigating the varying impacts of smartphone screen-time by gender, specifically how it is related to amount of time spent on different apps and activities, such as for communication purposes, entertainment, education, and so on. Considering the lack of overview on long-term effects (Boers et al., 2019) longitudinal studies may also offer more insight into the causal nature of the relationships between sleep, smartphone use behaviour and youth well-being.

In conclusion, the current research is one of the first to examine the mediating role of objectively measured sleep on the relationship between duration of smartphone-based screen-time and youth mental health. Specifically, the present study highlighted that reductions in sleep duration and increases in time spent on the device are associated with poor outcomes, in particular externalizing symptomatology. This methodology using innovative mobile sensing offers an advancement in approaches to measure sleep in youth.

The results can provide valuable information that can be integrated into educational initiatives aimed at youth, as well as interventions that target problematic or excessive smartphone use. More research into the interplay of these factors may be beneficial, to improve the understanding of real-life behaviour as it relates to mobile devices and sleep, and to promote better mental health outcomes in youth.

CHAPTER 4. GENERAL DISCUSSION

4.1 Summary of Objectives and Findings

The present Masters' thesis aimed to advance the scientific knowledge regarding the impact of smartphone use on the mental well-being of youth and investigated whether sleep mediates this relationship. It represents the first study to do so utilizing objectively measured sleep and smartphone use through mobile sensing technology.

Previous research has provided support for an association between youth mental health and smartphone use, while suggesting that different types of device use may have a differential effect on well-being, such as using a mobile phone for social interactions. Furthermore, many of the previous studies employed subjective assessments of behaviour, which may not provide accurate information. As such, the first study included in the thesis examined whether (1) an increase in objectively measured duration of smartphone-based screen-time would be associated with an increase in externalizing and internalizing symptomatology, (2) an increase in device unlocks, linked to social activities on smartphones, would be associated with better mental health outcomes, and (3) there would be a significant interaction between the two types of smartphone use, such that number of unlocks would lessen the strength of the association between screen-time and poor mental health outcomes.

The results, for the most part, provided support for these hypotheses, underscoring that overall time spent on mobile phone appears to be a passive and detrimental form of smartphone use, associated with more pronounced internalizing and externalizing symptoms, while frequent checking of the device (number of unlocks), associated with social interactions, is a more active form, linked to less internalizing symptoms. Moreover, we found a significant interaction between screen-time and number of unlocks, such that for youth with high screen-time, frequent checking of the device was linked to increases in externalizing symptoms, while for those with lower screen-time, the number of unlocks was associated with a decrease in externalizing symptoms.

Previous studies examining the relationship between smartphone use and youth mental health have also highlighted sleep as an important factor that may help explain this association. As such, the second study included in the thesis investigated whether a reduction in the duration of objectively measured sleep would mediate the relationship between objectively measured smartphone use and youth mental well-being. Consistent with previous research, the results of the second study supported, for the most part, this hypothesis, suggesting that objectively measured sleep significantly mediated the association between externalizing symptoms and objective smartphone use, underscoring that reductions in sleep duration can be detrimental for youth well-being. The mediation model accounted for 10.5% of the variance in externalizing, and while other additional factors might impact these symptoms as well, smartphone use and sleep routines represent behaviours that can be addressed through psychoeducation and public policies, and changing them could enhance mental health.

4.2 Future Directions and Clinical Implications

Considering the ubiquity of smartphones and their integrated use into daily routines and modern sleeping habits, it is imperative that these behaviours are thoroughly investigated in order to ascertain their impact on well-being, along with creating more public awareness and educational initiatives that enhance youth resilience, development and their overall mental health.

While mobile sensing offers a low-burden and easily scalable method of assessing behaviour and sleep, future research should take into account its limitations and should seek to augment collected data through multi-method investigations that address some of the deficiencies. For example, a mobile sensing sleep algorithm may be more suitable for digitally native younger individuals and be less reliable for older users due to differences in use and reliance on the device. Adding additional measures, such as different devices (i.e., smartwatches) or surveys, would help to confirm the accuracy of the estimates. Corroborating the information through multiple sensors (such as ambient noise, light, location), would also increase the reliability of the algorithm and provide a more nuanced image of the contextual information. Validating the algorithm through comparison with established approaches, such as polysomnography and actigraphy, would improve its accuracy. Considering that the present algorithm does not monitor the number of sleep interruptions at night or sleep latency, these assessments could be added to increase its complexity and efficiency in evaluating sleep-wake rhythms. The validity of these additions could be verified by comparison through other portable technologies such as the actigraph, smartphone sensors, or other activity monitors. In addition, we must note that mobile sensing sleep might also be less suitable for persons that do not have conventional sleep patterns or who work in shifts, since it targets night-time sleep episodes.

The daily routines of youth have been disrupted in many ways by the pandemic, with negative impact on their mental well-being (Gallagher et al., 2020; Raw et al., 2021). These disruptions have manifested in increased screen-time (Ribner et al., 2021; Saadeh et al., 2021) and sleep problems (Becker & Gregory, 2020; Carroll et al., 2020). Thus, the results of the present research conducted during the pandemic might not fully reflect the behaviours of youth post-pandemic.

Future research could examine the differences between pre-pandemic screen-time and sleep behaviours, compared to post-pandemic observations. Furthermore, future studies should further strive to obtain representative samples, along with detailed information on motives of use, in order to disentangle active and passive types of screen-time, through qualitative surveys and quantitative monitoring of patterns of behaviour, preferably over longer periods of time, to assess changes and causal relationships. The systematic review conducted by Seabrook et al. (2016) has emphasized that motives of use can moderate outcomes and that often times, the perception of support during social interactions can have significant impact, so the examination of the content of communication through technology becomes particularly salient. Such investigations would provide a clearer picture of how youth are using their phone naturalistically, and whether this use is linked to managing negative emotions and stressors, or whether the remote social interactions are protective or provide an outlet for mental health difficulties, such as enabling individuals affected by social anxiety to connect to others in a more comfortable manner. These observations would also enable clinicians to work collaboratively with youth and families, to provide interventions and psychoeducation on the potential benefits and harms of smartphone use, along with coping strategies to relieve the effects of excessive or problematic use.

The essential role that sleep plays in neurodevelopment and overall well-being makes it another important factor that has to be kept in mind. Young people that already have other mental health difficulties might be particularly vulnerable to altered sleep patterns, so it is important that clinicians assess sleep behaviours and daytime tiredness caused by night-time smartphone use in children and adolescents. In addition, parents can also provide education and monitor changes in daytime behaviour and mood.

Some authors (Vernon et al., 2018) recommend that physically removing the device at bedtime might diminish risks of problematic use. It might also be beneficial to young individuals impacted by sleep disruptions due to fear of missing out or those that are victims of cyberbullying. Godsell & White (2019) emphasize that adolescents are highly susceptible to peer influences when it comes to reductions in sleep and that parental involvement in sleep behaviours could help counteract some of these influences and enable more quality sleep. Such an intervention could be appropriate for children and adolescents, while young adults could benefit from psychoeducation regarding sleep hygiene and development of coping skills to counteract peer pressure

Large studies conducted during the pandemic (Nagata et al., 2021) have suggested that the increases in smartphone use that happened during restrictions remain even after they are lifted, findings that re-affirm the need for interventions in order to obtain more moderate use or less displacement of wellness promoting behaviours. Liu et al. (2019) observed that some of the problematic effects of excessive device use may be reversed through an intervention that increases exercise, with significant effects; given this evidence, there is reason to assume that sleep interventions might also be effective in youth to counteract the damaging aspects and enhance well-being. To make them more compelling, these interventions could also be effectively delivered through the smartphone itself, which would also allow for initial assessment of behaviour, along with objective monitoring of compliance and changes in behaviour over time.

In conclusion, the findings detailed in this thesis may advance the understanding of researchers and clinicians with regard to the detrimental effects of excessive smartphone use and may provide a basis for future interventions and policy changes that can be implemented to enhance youth well-being, as well as provide valuable information to educators, parents and youth themselves. Encouraging more healthy behaviours and a reduction in excessive smartphone use, especially at bedtime, could have positive effects on youth mental health. Given the ubiquity of mobile devices, they can also be used to enhance monitoring of daily behaviours or to deliver interventions, which would open new avenues for treatment, in a low-burden, naturalistic manner. Finally, to disentangle the complex interplay between sleep, youth mental health and smartphone use behaviour, more research would be beneficial, especially studies that would provide more insight into the motives of use, through a combination of subjective and objective measures.

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Appendix

Table 2.1

Sociodemographic characteristics of participants

Characteristic	*n*	%	Total
Biological Sex			451
Female	375	83	
Male	76	17	
Phone Type			451
Android	118	26	
iOS	333	74	
Mental Health History			451
Yes	91	20	
No	360	80	
Mother's education			451
Did not finish High school	22	5	
Finished High school	79	18	
Further education	97	21	
University	244	54	
I don't know	4	<1	
Prefer not to answer	5	1	

Table 2.2

Correlations between objective and subjective smartphone use measures

	Mean Screen-time	Number of unlocks
Talking on the phone with friends/family	-0.02	0.03
Video calling friends/ family	-0.02	0.02
Communicating via WhatsApp or text	0.11	0.18*
Communicating via social media	0.08	0.18*
Gaming with friends/ family	0.10	0.03
Time spent playing video or app games	0.20	-0.05
Watching films/Netflix/YouTube	0.08	-0.07
Listening to music	0.01	-0.04
Browsing the Internet	0.15*	0.01
Posting content online (TikTok/Instagram) or blogging	-0.06	-0.05

$^{*}p < .05$. $^{**}p < .01$.

Table 2.3

Regression results depicting associations between externalizing symptoms and predictors

Predictor	*b*	*b* 95% CI [LL, UL]	t	Fit
Step 1				
Mental Health Diagnosis	0.18**	[0.09, 0.28]	3.82**	
Biological Sex	0.01	[-0.08, 0.11]	0.25	
Mother's Education	-0.16**	[-0.25, -0.07]	-3.40**	
Phone Type	0.01	[-0.08, 0.11]	0.26	R^2 = .062** 95% CI[.02,.10]
Step 2				
Duration of Screen-time	0.19**	[0.09, 0.28]	3.76**	
Number of Unlocks	-0.10	[-0.21, 0.00]	-1.90	
Mental Health Diagnosis	0.18**	[0.09, 0.27]	3.80**	
Biological Sex	0.01	[-0.09, 0.10]	0.10	
Mother's Education	-0.14**	[-0.23, -0.05]	-3.01**	
Phone Type	0.01	[-0.09, 0.11]	0.13	
				R^2 = .094** 95% CI[.04,.14]

Note. b represents unstandardized regression weights. *LL* and *UL* indicate the lower and upper limits of a confidence interval, respectively.
* indicates $p < .05$. ** indicates $p < .01$.

Table 2.4

Regression results depicting associations between internalizing symptoms and predictors

Predictor	*b*	*b* 95% CI [LL, UL]	t	Fit
Step 1				
Mental Health Diagnosis	0.21**	[0.12, 0.30]	4.37**	
Biological Sex	-0.15**	[-0.24, -0.05]	-3.07**	
Mother's Education	-0.05	[-0.14, 0.04]	-1.05	
Phone Type	-0.13**	[-0.23, -0.04]	-2.83**	R^2 = .095** 95% CI[.04,.14]
Step 2				
Duration of Screen-time	0.14**	[0.04, 0.24]	2.77**	
Number of Unlocks	-0.12*	[-0.22, -0.02]	-2.27*	
Mental Health Diagnosis	0.21**	[0.11, 0.30]	4.33**	
Biological Sex	-0.15**	[-0.25, -0.06]	-3.23**	
Mother's Education	-0.04	[-0.13, 0.06]	-0.77	
Phone Type	-0.16**	[-0.26, -0.06]	-3.12**	
				R^2 = .116** 95% CI[.05,.16]

Note. *b* represents unstandardized regression weights. *LL* and *UL* indicate the lower and upper limits of a confidence interval, respectively.
* indicates $p < .05$. ** indicates $p < .01$.

Table 2.5

Regression results using externalizing symptoms as the criterion including an interaction term

Predictor	*b*	*b* 95% CI [LL, UL]	t	Fit
(Intercept)	-0.04	[-0.13, 0.06]		
Duration of Screen-time	0.22**	[0.12, 0.32]	4.26**	
Number of Unlocks	-0.13*	[-0.24, -0.03]	-2.46*	
Mental Health Diagnosis	0.19**	[0.09, 0.28]	3.96**	
Biological Sex	-0.00	[-0.10, 0.09]	-0.04	
Mother's Education	-0.15**	[-0.24, -0.05]	-3.14**	
Phone Type	0.02	[-0.08, 0.12]	0.44	
Mean Screen-time : Number of Unlocks	0.11*	[0.01, 0.20]	2.27*	
				R^2 = .105** 95% CI[.04,.15]

Note. b represents unstandardized regression weights. *LL* and *UL* indicate the lower and upper limits of a confidence interval, respectively.
* indicates $p < .05$. ** indicates $p < .01$.

Table 3.1

Sociodemographic characteristics of participants

Characteristic	***n***	**%**	**Total**
Biological Sex			407
Female	342	84	
Male	65	16	
Phone Type			407
Android	105	26	
iOS	302	74	
Mental Health History			407
Yes	85	19	
No	322	71	
Mother's education			407
Did not finish High school	19	5	
Finished High school	70	17	
Further education	91	22	
University	221	54	
I don't know	3	<1	
Prefer not to answer	3	<1	

Table 3.2

Regression results depicting associations between externalizing symptoms and predictors

Predictor	*b*	*b* 95% CI [LL, UL]	t	Fit
Step 1				
Mental Health Diagnosis	0.21**	[0.11, 0.31]	4.11**	
Biological Sex	0.03	[-0.07, 0.13]	0.58	
Mother's Education	-0.13**	[-0.23, -0.03]	-2.67**	
Phone Type	-0.03	[-0.13, 0.07]	-0.57	R^2 = .067** 95% CI[.02,.11]
Step 2				
Mean Smartphone Screen-time	0.14**	[0.04, 0.24]	2.79**	
Mental Health Diagnosis	0.20**	[0.11, 0.30]	4.08**	
Biological Sex	0.02	[-0.08, 0.12]	0.41	
Mother's Education	-0.12*	[-0.22, -0.02]	-2.42**	
Phone Type	-0.00	[-0.10, 0.10]	-0.05	
				R^2 = .086** 95% CI[.03,.13]

Note. b represents unstandardized regression weights. *LL* and *UL* indicate the lower and upper limits of a confidence interval, respectively.
* indicates $p < .05$. ** indicates $p < .01$.

Table 3.3

Regression results depicting associations between internalizing symptoms and predictors

Predictor	*b*	*b* 95% CI [LL, UL]	t	Fit
Step 1				
Mental Health Diagnosis	0.21**	[0.11, 0.31]		
Biological Sex	-0.14**	[-0.24, -0.04]		
Mother's Education	-0.02	[-0.12, 0.07]		
Phone Type	-0.15**	[-0.25, -0.05]		R^2 = .096** 95% CI[.04,.15]
Step 2				
Mean Smartphone Screen-time	0.08	[-0.02, 0.18]	1.60	
Mental Health Diagnosis	0.21**	[0.11, 0.31]	4.19**	
Biological Sex	-0.14**	[-0.24, -0.04]	-2.86**	
Mother's Education	-0.02	[-0.11, 0.08]	-0.36	
Phone Type	-0.14**	[-0.23, -0.04]	-2.70**	
				R^2 = .102** 95% CI[.04,.15]

Note. b represents unstandardized regression weights. *LL* and *UL* indicate the lower and upper limits of a confidence interval, respectively.
* indicates $p < .05$. ** indicates $p < .01$.

Table 3.4

Mediation analysis results, average sleep per day as mediator

Path	Estimate	*SE*	95% CI [LL, UL]	*p*
Direct (c)	0.100	0.059	[-0.011, 0.217]	0.090
Indirect (a*b)	0.042*	0.019	[0.009, 0.081]	0.027
Total (c+a*b)	0.142**	0.055	[0.034, 0.251]	0.009

Note. LL and *UL* indicate the lower and upper limits of a confidence interval, respectively.
* indicates $p < .05$. ** indicates $p < .01$.

Table 3.5

Mediation analysis results, average sleep during weekdays as mediator

Path	Estimate	*SE*	95% CI [LL, UL]	*p*
Direct (c)	0.088	0.056	[-0.020, 0.205]	0.115
Indirect (a*b)	0.035*	0.017	[0.007, 0.075]	0.036
Total (c+a*b)	0.123*	0.052	[0.030, 0.236]	0.019

Note. LL and *UL* indicate the lower and upper limits of a confidence interval, respectively.
* indicates $p < .05$. ** indicates $p < .01$.

Table 3.6

Mediation analysis results, average sleep during weekends as mediator

Path	Estimate	*SE*	95% CI [LL, UL]	*p*
Direct (c)	0.111	0.052	[-0.008, 0.225]	0.058
Indirect (a*b)	0.030*	0.015	[0.008, 0.066]	0.047
Total (c+a*b)	0.169**	0.050	[0.066, 0.272]	0.001

Note. LL and *UL* indicate the lower and upper limits of a confidence interval, respectively.
* indicates $p < .05$. ** indicates $p < .01$.

Figure 1

Figure depicting examples of interfaces of the PROSIT app

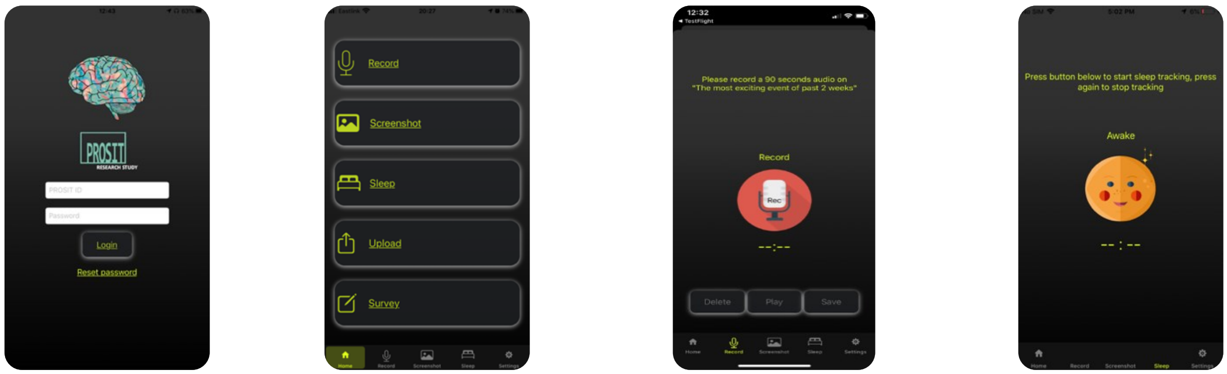


Figure 2

Histogram depicting frequency of participants included in the analysis, by month of recruitment

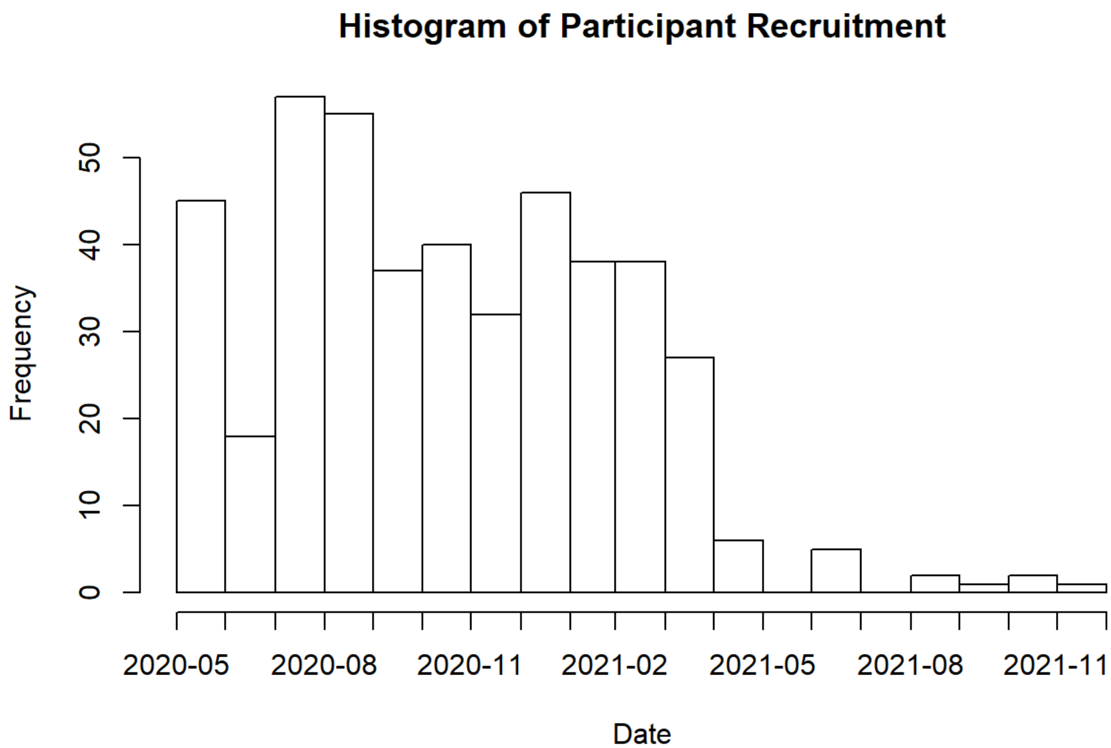


Figure 3

Histogram depicting frequency of scores, Internalizing factor

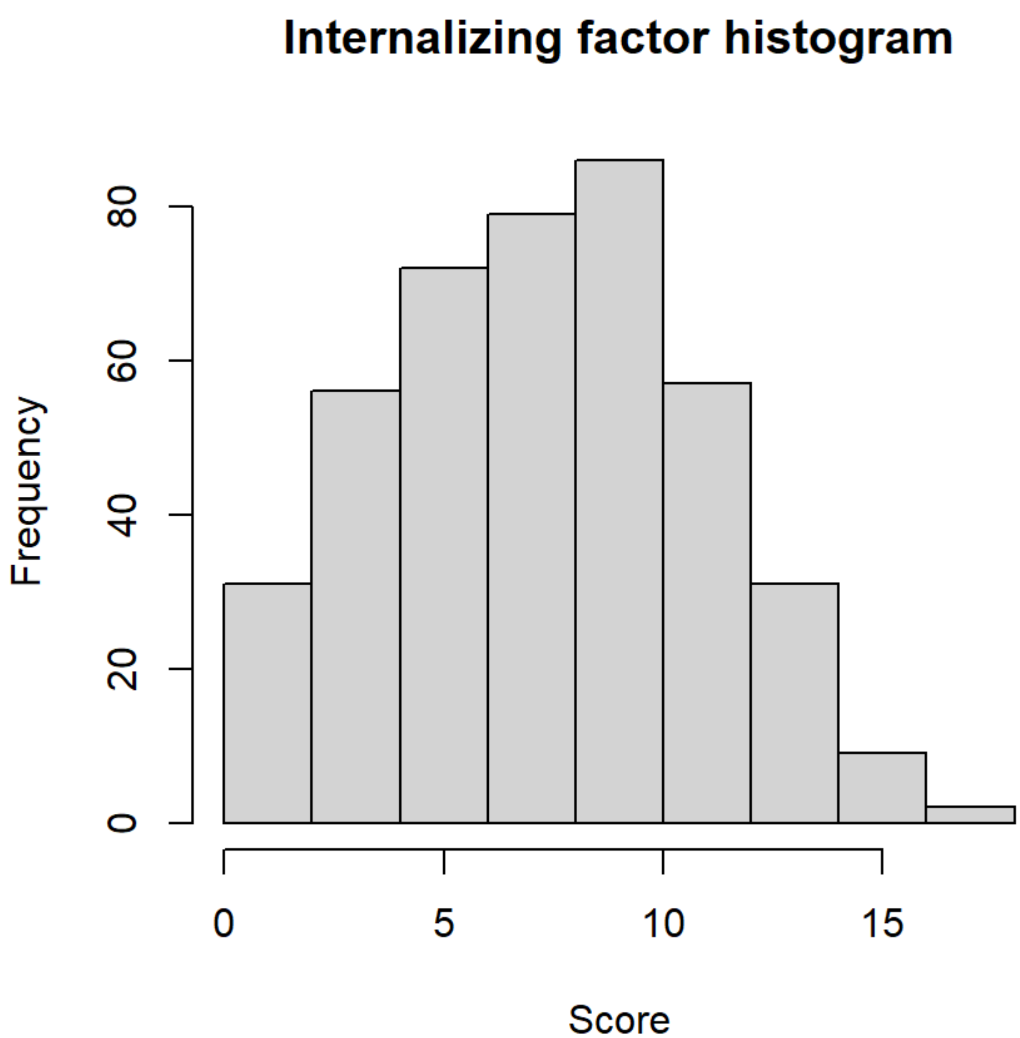


Figure 4

Histogram depicting frequency of scores, Externalizing factor

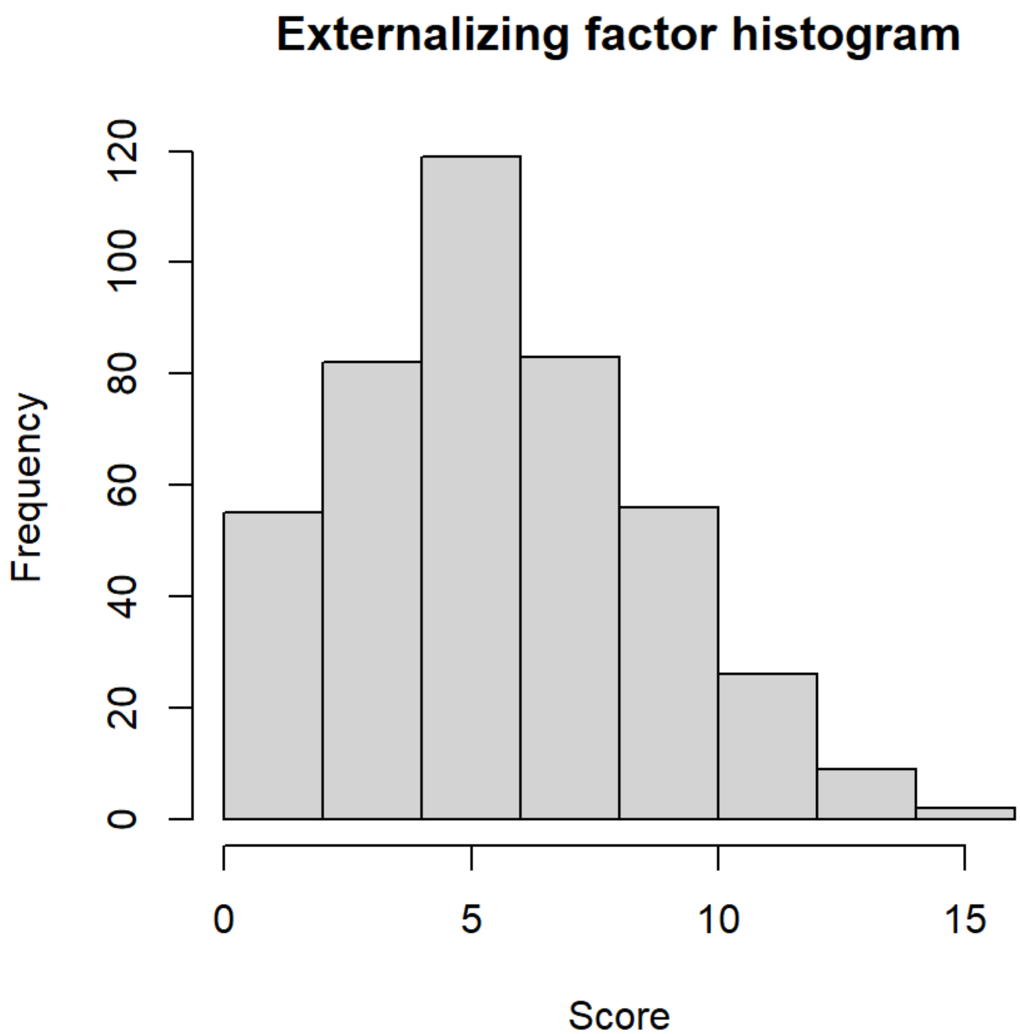


Figure 5

The interaction between mean screen-time and number of unlocks predicting externalizing symptoms

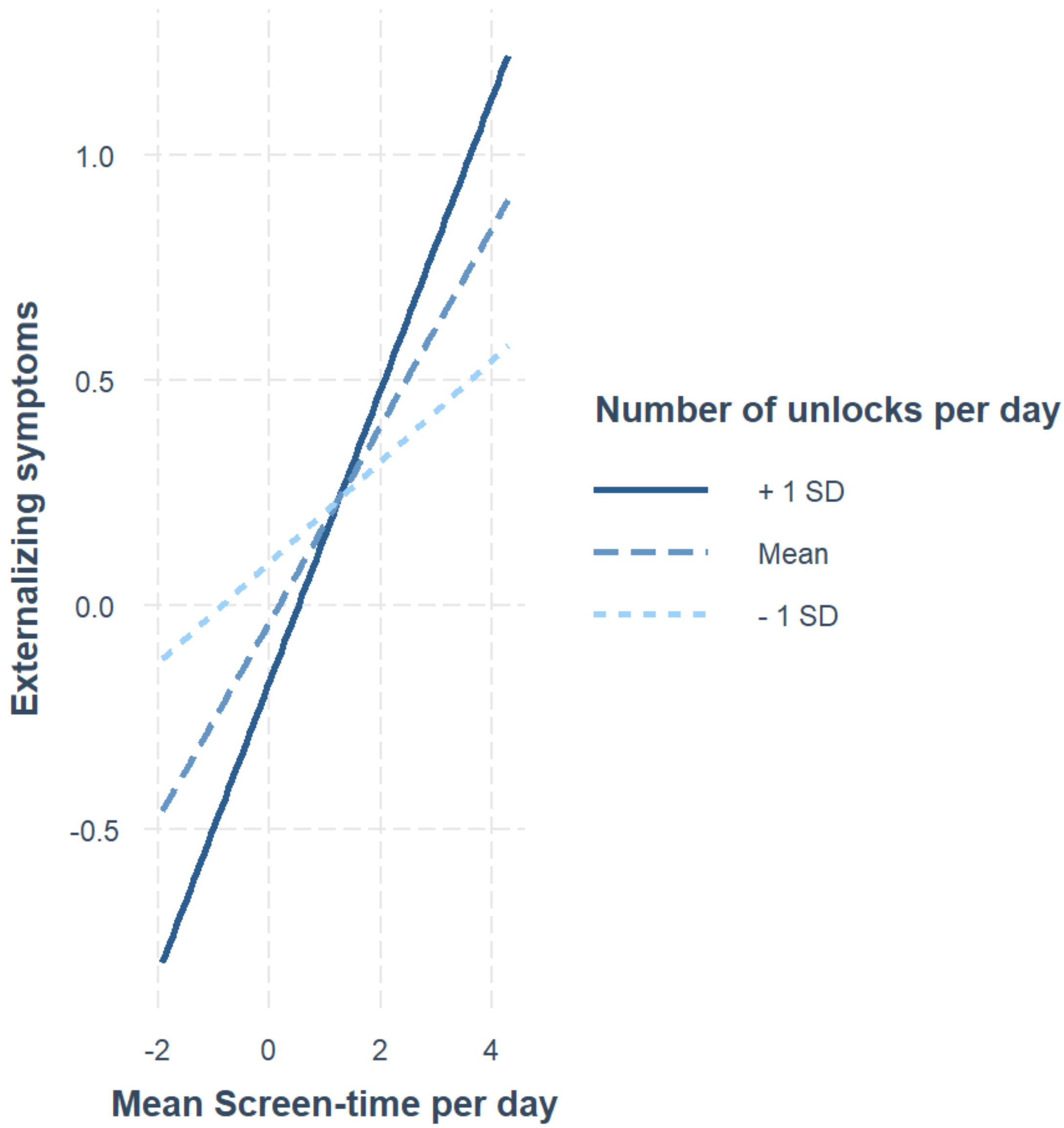
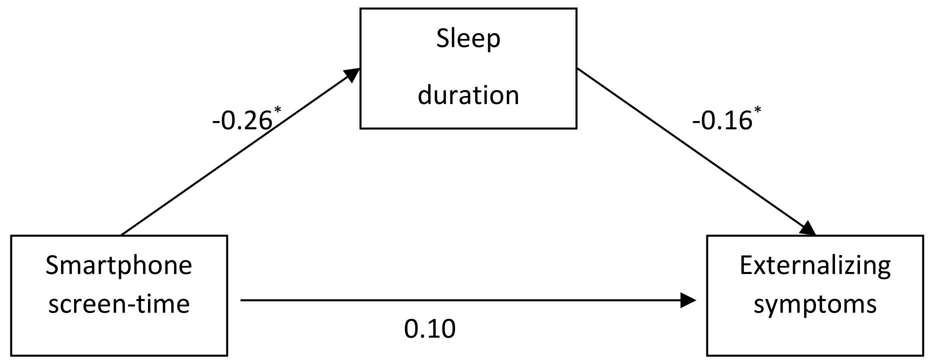


Figure 6

Figure depicting sleep as mediator of the relationship between duration of smartphone-based screen-time and externalizing symptoms, using standard coefficients



Note. * $p < .05$