MOBILE SENSING AND YOUTH MENTAL HEALTH DURING THE COVID-19 PANDEMIC: A PILOT STUDY

by

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ABSTRACT

During the COVID-19 pandemic mental health concerns were exacerbated demonstrating a need for mental health data to be collected on a large-scale and in an affordable form. The study piloted the use of a mobile sensing application in youth with and without psychiatric disorders. The study aimed to determine if smartphone-based physical activity data can predict depression, anxiety, and changes in symptoms. 122 youth self-reported symptoms of anxiety, depression at baseline, and follow-up. An application was installed which measured physical activity (GPS) for two-weeks. The study demonstrated that smartphone mobile sensing is feasible in youth. GPS data did not explain baseline symptoms; however, it helped predict changes in symptoms. The study provided preliminary information on mobile sensing in youth, and the potential for it to predict changes in symptoms. The study reiterates the need for larger studies with standardized measures in the field of smartphone mobile sensing.

LIST OF ABBREVIATIONS USED

ADHD	Attention-Deficit/Hyperactivity Disorder
ADHD-SR	Attention-Deficit/Hyperactivity Disorder Self-Report
CES-DC	Center for Epidemiologic Studies Depression Scale
GPS	Global Positioning System
IWK	Izaak Walton Killam Health Centre
PA	Physical Activity
PROSIT	Predicting Risk and Outcomes of Social InTeractions
REDCap	Research Electronic Data Capture
SCARED	Screen for Child Anxiety Related Emotional Disorders

CHAPTER 1 INTRODUCTION

Globally, there has been an estimated 10-20% of youth[1] suffering from a psychiatric disorder (Kessler et al., 2007; Polanczyk et al, 2015). The onset of most psychiatric disorders occurs in youth, and the prevalence of these disorders is continuing to rise (Comeau et al., 2019). Anxiety and depression are common psychiatric disorders in youth, at a prevalence of 31.9% and 11.7%; collectively impacting health and well-being (Boak et al., 2016; Ialomiteanu et al., 2016; Merikangas et al., 2010; Polanczyk et al, 2015). Psychiatric disorders are underdiagnosed and undertreated, there is a need to close the treatment gap and globally reduce the burden of psychiatric disorders (Frankish et al., 2018, ; Georgiades et al., 2019; Hintzpeter et al., 2015; Kessler et al., 2007; Vos et al., 2017).

During the COVID-19 pandemic, mental health concerns were exacerbated - there were documented increases in depression, anxiety, suicidal ideation, and substance use (Adams-Prassl et al., 2020; Brooks et al., 2020; Czeisler et al., 2020; Pierce et al., 2021; Thorisdottir et al. 2021; Zeytinoglu et al., 2021). Mental health symptoms worsened across all age groups, especially in youth (Liang et al., 2020; Thorisdottir et al. 2021; YoungMinds, 2020; Xie et al., 2020). Considering the vulnerability of youth, and lack of proper care there is a need for effective early intervention and prevention programs for youth at risk for anxiety and depression (Comeau et al., 2019; Georgiades et al., 2019)

To develop interventions and prevention programs, data on symptoms of anxiety and depression must be obtained in an accurate and timely manner. Due to the global mental health crises and treatment gap, there is also a need for the data to be collected on a large-scale and

[1] Youth in the current study were 10-21 years of age. 21 representing the beginning of adult life in the United States of America. There is no universally agreed upon definition for the term "youth" (https://www.un.org/en/global-issues/youth), therefore it may vary for the studies referred to in this literature review.

affordable form. With mobile sensing, data can be collected remotely and passively through smartphones, opening new avenues for an accurate, timely, economical, and large-scale objective measure (Aung et al., 2017; Grünerbl et al., 2015; Lind et al., 2018; Onnela & Rauch 2016). For the purpose of this review, the term 'mobile sensing' refers to data collected through smartphones, and no other mobile devices. Currently, clinicians rely on patients' personal and subjective symptom ratings obtained during routine clinical care. This approach may be unreliable because of inaccuracy in retrospective reports and the risk of reporting biases related to current symptom severity, cognitive distortions, and environmental stressors (; Goldfarb et al., 2017; Wells & Horwood, 2004). With mobile sensing, changes in behaviour and movements can be tracked in real time using existing smartphone sensors. This includes the global positioning system (GPS), accelerometer (measures acceleration), gyroscope (measures rotation), and phone usage data (call and message logs). These sensors can be used to identify changes in behaviour, mirroring core clinical dimensions of several psychiatric disorders, including depression, anxiety, bipolar disorder, and schizophrenia (Ben-Zeev et al., 2016; Chow et al., 2017; Faurholt-Jepsen et al., 2015; Faurholt-Jepsen et al., 2020; Henson et al., 2020; Jongs et al., 2020; Ranjan et al., 2019; Saeb et al., 2015). For example, through smartphone technology, it can be observed how proxies of sedentary behaviour mirror anxiety symptoms (Chow et al., 2017; Saeb et al., 2015).

Mobile sensing technology has experienced vast improvements over the past decade. In 2008, mobile sensing devices were similar to a pager, a wireless device that could be clipped onto a belt loop (Tanzeem et al., 2008). Now Mobile sensing can be done through the sensors in smartphones, including Android and iOS devices. This is particularly convenient because it is currently estimated that 75-94% of youth aged 10 to 18 years own a smartphone, making mobile sensing a highly economical option (Berg, 2019; Vernon et al., 2018). There is no need to purchase an additional device; a special application can be simply downloaded onto their phone, which gathers the relevant data and relays it to secure servers. This method of data collection imposes no additional burden on youth; data is tracked and gathered with little to no involvement by the participant. Exploring the use of mobile sensing technology is of particular interest, as it offers great potential as an objective clinical monitoring tool for youth at risk for anxiety and depression (Aung et al., 2017; Lind et al., 2018).

1.1 Tracking Physical Activity with Mobile Sensing

Mobile sensing technology can track social activity (call & text logs), social media and application usage, sleep, physical activity (PA), and many other variables (Onnela & Rauch, 2016). Mobile sensing can track PA behaviours such as distance traveled, locations visited, and time at home (Chow et al., 2017). The built-in sensors of smartphones commonly used to track PA are GPS, accelerometer, gyroscope, and magnetometer. PA is one of the most frequently assessed measures, and one of the most reliable mobile-sensed predictors of anxiety and depression symptoms (Cornet & Holden, 2018; Rohani et al., 2018). However, without the addition of wearables for example heart rate cannot be measured by built-in sensors of smartphones making it difficult to estimate the intensity of the PA.

PA is of further specific interest because of its connection to mental health and well-being (Cornet & Holden, 2018; Rohani et al., 2018). Despite the promise of mobile sensing, and the importance of PA for mental health, there are few studies to look at mental health and mobile sensing in youth (Cao et al., 2020). Previous mobile sensing research has found age-related differences in PA, with samples ranging from 18-90 years old, specfically in the measure of entropy (See page 6). This phenomenon warrants the need for data in the context of youth participants (Cao et al., 2020; Jongs et al., 2020). The rationale for the need to expand research on objective measures of PA in youth is based on two additional factors: the established positive association of good mental health outcomes and high PA levels in self-reported data in youth (Feng et al., 2017). PA is also used as a treatment method for depression *(*Kvam et al., 2016*)*.

1.2 Physical Activity and Mental Health

The importance of PA in youth has been demonstrated in self-reported data. Physical inactivity in youth, defined as youth not meeting suggested guidelines for PA, is associated mental health issues (Thivel et al., 2018). Physical inactivity—has a lot to do with sedentary lifestyles of youth. For example, a sedentary behaviour can be that someone is sitting or lying down with minimal energy expenditure (Thivel et a., 2018). According to the displacement hypothesis, rather than being physically active, youth self-report spending time sitting in front of screens (Chen et al., 2020; Kraut et al., 1998; Mutz et al., 1993). Such sedentary behaviour has been shown to increase the risk for anxiety and depression (Feng et al., 2017; Hamer et al., 2014; Sui et al., 2015; Teychenne et al., 2015; Zhai et al., 2015). Findings for the association of anxiety with sedentary behaviour are more limited than depression. A systematic review by Teychenne et al., (2015) established moderate evidence for a positive association between overall sedentary behaviours and anxiety. However, PA studies utilizing self-report data have been shown to have low accuracy for light daily activities and sedentary behaviours (Matthews et al., 2012). This could mainly be due to the unstructured nature of these behaviours, giving self-report data for light PA and sedentary behaviour low test-retest reliability. In these scenarios, mobile sensing technology could greatly improve the reporting of PA.

Clinicians commonly see a lack of PA in patients suffering from depression. There is evidence for a bidirectional relationship between PA and depression, meaning that lack of PA may increase the risk for depression, but also depression may lead to lack of ability to engage in PA (Kandola et al., 2020, McKercher et al., 2014; McMahon et al., 2017; Roshanaei-Moghaddam et al., 2009; Schuch et al., 2017). Therefore, improving PA is often an important component in the clinical management of depression and anxiety in youth. Improving PA is part of Cognitive Behavioural Therapy, more specifically, it is one element of behavioural activation techniques. These techniques are evidence based and are used as healthy coping mechanisms to decrease symptomology and improve quality of life (LeBouthillier & Asmundson, 2017; Oeland et al., 2010; Veale, 2008; Watkins, 2003). Individuals with depression are less likely to engage in activities that bring positive reinforcement or satisfaction. Therefore, through behavioural activation, patients are encouraged to participate in activities they may be avoiding in order to restore physical movement. In addition, a meta-analysis concludes that PA is an effective treatment for depression on its own, as well as in conjunction with antidepressant medication (Kvam et al., 2016). The mechanisms through which PA can improve mental health and support clinical management include multiple biological and psychological pathways (de Sousa et al., 2017; Kandola et al., 2019; Kredlow et al., 2015; Spruit et al., 2016; Tang et al., 2010). These pathways include, but are not limited to: improvement in self-concept, self-esteem, self-efficacy, social support, academic performance, sleep, neuroplasticity, and inflammation.

1.3 Previous Research on Mobile Sensing in Youth

Mobile sensing research in youth is limited. Very recently, a landmark study concluded that smartphone mobile sensing is necessary and feasible in pediatric samples as an objective measure for screen time (Wade et al., 2021). Mobile sensing was found to be a low-burden approach to data collection that can potentially be implemented in longitudinal research of cohorts up to 12,000 youth participants. However, the first and only study to examine mental health and mobile sensing PA in youth is Cao et al., (2020). This recently published preliminary study included 11 adolescents with major depressive disorder and a comorbid diagnosis of anxiety. Mobile sensing data was collected for two months on an Android-only application. The application tracked movement type (walking, driving), distance moved, steps, transition time, location variance, entropy, places visited, and time spent at home. Entropy is the uniformity in time spent at frequently visited locations each day. It is used to better understand how much time people are spending outside of their common locations for example, home, work, and school. Low entropy indicates a person spends little time outside of their common locations and are restricted to a small number of places they spend time at. In previous research, low entropy is associated with overall lower mobility and more time at home (Jongs et al., 2020). In the study on youth by Cao et al. (2020) found there was a negative correlation between symptoms and PA; participants high in depression symptoms had lower overall mobility and were taking fewer daily steps. There was not a significant correlation between depression ratings and number of places frequented or lower location variance. In contrast there was also a positive correaltion between symptoms and entropy; the participants high in depression had higher entropy in the places they visited. This contradicted previous research in adults but was in line with results from Jongs et al. (2020) that found age related differences in entropy. The posititve association of high depression and high entropy does not have a clear interpretation, indicating more research is needed to understand PA behaviour patterns and mental health in a youth population. In conclusion, the study provides helpful preliminary data on mobile sensing in a young population but is limited by its small sample size of 11 participants.

1.4 Previous Research on Mobile Sensing and Physical Activity in Adults

1.4.1 Bipolar Disorder. A lot of research on mobile sensing of PA has been conducted in adult patients with bipolar disorder. Small studies of patients with bipolar disorder have found mobile sensing PA data to have an inverse correlation with symptoms of depression (Beiwinkel et al., 2016; Faurholt-Jepsen et al., 2014; Grünerbl et al., 2015; Maxhuni et al., 2016; Osmani, 2015). Mobile sensing PA can detect bipolar states and state changes. For example, when bipolar patients are more active, they are likely to be in a manic state, and when activity is low, they are likely to be in a depressive state. Most recently, in 2020, a randomized controlled trial found that bipolar patients in the smartphone-based group reported higher quality of life and reduced stress in comparison to patients in standard treatment (Faurholt-Jepsen et al., 2020). PA levels were not specifically analysed. There was no effect on clinically rated depressive and manic symptoms. The lack of effect could be due to the impacted variable not being measured, such as mood stability or illness insight. More research is needed to fully understand its ability to help bipolar patients.

1.4.2 Anxiety. Previous studies have used the smartphone's GPS sensor to study movement patterns associated with symptoms of anxiety (Boukhechba et al., 2018; Chow et al., 2017; Gong et al., 2019). Studies of undergraduate students have investigated the association of social anxiety and GPS locations (Boukhechba et al., 2018; Chow et al., 2017). Time at home was considered to social isolation relative to other locations. Those high in social anxiety were found to be more likely to avoid public places and go out less on weekends and evenings. They were also found to spend more time at home after 4:00 pm, which coincides with many participants returning home from class. PA as measured by GPS mobile sensing data strongly reflects the symptoms of students with social anxiety, GPS location data was able to predict social anxiety levels with an 85% accuracy rate.

1.4.3 Depression. Mobile sensing research in depression revealed that those with symptoms of depression are more likely to experience irregular and lower daily activity rates, in addition to more time at home (Laiou et al., 2021; Sarda et al., 2019). GPS data such as sequence of places visited, distance traveled, distance from home, and number of places visited have been used in statistical models to detect when users were experiencing depressed mood, with few false alarms (Canzian & Musolesi, 2015; Narziev et al., 2020). Mobile sensing has not consistently derived meaningful results from studying the correlation of GPS mobility data and depressive symptoms (Chow et al., 2017; Place et al., 2017; Saeb et al., 2017). Research has attempted to find meaningful context to GPS data by taking a closer look at anxiety, depression, and semantic location (Saeb et al., 2017). To derive semantic location, participants coded GPS locations with the type of location (home, work etc.). Despite the additional data context, the study was able to establish very few relationships between location type and depression and anxiety. Correlations between self-reported anxiety and depression and time spent at certain location types are weak and inconsistent. The inconsistency in findings is likely since depression and mobile sensing research is a new and growing area of research without established standardized measures. As well, depressive symptoms may present differently in patients with atypical and typical depression creating individual differences (Singh & Williams, 2006). For example, those with atypical depression, may sleep more at night and during the day in comparison to those with typical depression. The differences in depression symptoms across individuals may make statistical models more difficult or complex (Aung et al., 2017).

1.4.4 COVID-19. During the COVID-19 pandemic there were changes in PA levels. In one study on students in Pennsylvania, step counts were found to decline more than 50% in comparison to pre-pandemic levels, as measured by a Fitbit watch (Giuntella et al., 2021). In the same study, out of lifestyle factors (PA, sleep, heartrate) the decrease in PA was found to be a leading factor associated with increased depression during the pandemic. Changes in PA and mental health have been also detected in real time using mobile sensing (Huckins et al., 2020). PA included number of locations visited and distance traveled. There was an increase in symptoms of anxiety and depression, as well as an increase in sedentary time. Overall, mobile sensing offers great insight into PA changes during the pandemic. In conclusion, previous research on mobile sensing and PA demonstrates potential utility in youth. It has the ability to assess changes in anxiety and depression, however there are still many limitations to this research.

1.5 Limitations of Current Research on Mobile Sensing and PA

1.5.1 Lack of Research on Youth. Mobile sensing research on youth is limited (Lind et al., 2018). Only recently has one study been published looking at automatically generated mobile sensing PA levels and psychiatric disorders in youth (Cao et al., 2020, Melbye et al., 2020). Youth offer a prime research population because they are active mobile phone users who have a strong attachment to their devices (Berg, 2019; Ventä et al., 2008). Mobile sensing offers an economical option as an objective measure since youth do not require an additional device as participants or patients. More research is needed to fully understand how effective mobile sensing technology could be in measuring of symptoms of anxiety and depression in youth (Lind et al., 2018). In some cases, the correlation of PA and depression in youth has been found to contrast adults. Youth high in depression had high entropy in the places they visited, and vise versa for adults (Cao et al., 2020; Jongs et al., 2020; Saeb et al., 2015). In addition, more research is also needed to fully understand how clinical and general youth populations feel about mobile sensing in terms of privacy and level of comfort (Nicholas et al., 2019).

1.5.2 Lack of iOS Mobile Sensing Applications. Most current mobile sensing applications are limited to Android devices, with only a couple using both iOS and Android compatible applications (Boukhechba et al., 2018; Gong et al., 2019). There is a need for more studies to encompass iOS devices, to make for a more representative sample and limit bias. Users of iOS and Android devices have also been found to differ slightly in socioeconomic status, personality, and privacy concerns (Benenson et al., 2013; Götz et al., 2017). For example, people interested in technology are more likely to have an Android device. iOS and Android devices differ in number of sensing types and sensor calibration, it is possible device differences can lead to bias (Kuhlmann et al., 2021). iOS devices are very popular, up to 60% of Canada's youth have an iOS device (Afilias Technologies Limited, 2019). Without iOS-compatible mobile sensing applications, there is a large percentage of the population being excluded from participating in mobile sensing research.

1.6 The Current Study

The present study explored the (prospective) relationship of mobile sensing PA data with depression and anxiety in the context of the COVID-19 pandemic. The pilot study expanded the current literature on mobile sensing in youth patients, and youth in the general population (ages 10-21).

The overarching aim of the study was, firstly, to pilot the use of a novel mobile sensing application in youth participants with iOS and Android devices. Secondly, to determine if smartphone-based PA data can explain unique variation in depression and anxiety scores, and changes in scores over time, even after accounting for comorbid disorders common in youth. Disorders included depression, anxiety, and attention-deficit hyperactivity disorder (ADHD). ADHD was also controlled for as a comorbid disorder, as it is a common psychiatric disorder in youth (Polanczyk et al, 2015). The study was designed to have two time points: baseline and a three-month follow-up (for timeline of study see Table 1). At baseline, the participants completed a self- report mental health assessment and were tracked for 14-days using a mobile sensing application. PA data were derived from GPS, which provided three variables; time at home, distance traveled, and number of locations visited (Cao et al., 2020; Chow et al., 2017; Huckins et al., 2020). At the 3-month follow-up, a self-report mental health assessment was completed. Based on previous research the following three hypotheses were made:

1.6.1 Hypothesis One: It was hypothesized that youth with and without psychiatric disorders would be able download a mobile sensing application and complete 14-days of data collection. Participants would report minimal issues and privacy concerns with the application.

1.6.2 Hypothesis Two: It was hypothesized that baseline PA data (mean daily time at home, distance traveled, and number of locations visited) would predict unique variance self-reported anxiety and depression at baseline, over and above demographic (gender, age, socioeconomic status) and control variables alone (timepoint during pandemic, phone type, comorbidities of other disorders ADHD, depression, anxiety).

1.6.3 Hypothesis Three: It was hypothesized that baseline PA data (mean daily time at home, distance traveled, and number of locations visited) will predict unique variance in the total change in scores (delta y) on the scale for anxiety and depression from baseline to three-month follow-up, over and above demographic and control variables alone.

CHAPTER 2 METHODS

2.1 Participants

2.1.1 Recruitment. Between February and July 2020, the study recruited youth from the general population, as well as youth from a clinical population. The study recruited from both populations and aimed to identify symptoms of anxiety and depression in youth without the need for them to have a previous clinical assessment and diagnosis (Davis et al., 2018; Purves et al., 2020). The study is able address shortcomings of previous research by including those that may not have access to mental health care or are living in a remote area (Cao et al., 2020; Corey & Keyes, 2002; Salari et al., 2020). There was not a clinical cut off to enroll in the study in order to examine depression and anxiety dimensionally and increase statistical power within the study. In addition, to capture the fluctuations in symptoms over time, for example, participants that went from healthy at baseline to having developed symptoms of anxiety or depression at follow-up, in order to better understand if PA would explain the change (Davis et al., 2018).

Participants were recruited online across Canada from Kijiji and social media platforms, including Instagram, Twitter, and Facebook (For recruitment material see Appendix A, Appendix B, Appendix C). Social media recruitment targeted those with a psychiatric disorder, although there was no clinical cut off to enroll in the study. Participants were also recruited in Nova Scotia, Canada from the Izaak Walton Killam (IWK) Health Centre, under the supervision of Dr. Sandra Meier and Dr. Alexa Bagnell (approximately 10% of the sample). Posters were set up in the waiting areas of the clinic, in addition to clinicians providing their patients with brochures on the study.

An a-priori power analysis was calculated for a linear multiple regression using G*Power software. The parameters included an alpha of 0.05, a desired 80% power, and an effect size of f^2

=0.06, and 10 predictors. The effect size was estimated from previous studies that found a small correlation between depression and distance traveled and time at home (r=0.22-0. 23 was converted to f^2) (Saeb et al., 2015, Saeb et al., 2016). The aim was a sample size of 130 participants. The study aimed to recruit approximately 145 youth to compensate for an expected 10% loss at follow-up.

2.1.2 Inclusion Criteria. The study included English-speaking youth and adolescents; ages 10-21 years old. The cut off of 21 years if age was used to focus on a young population, up until the legal drinking age in the United States of America (USA). Participants were required to live in within Canada or the USA and own a smartphone. Prior to filling out self-report questionnaires of symptoms in the past three months participants indicated if they have ever been diagnosed with a mental disorder.

2.1.3 Exclusion Criteria. The study excluded those in inpatient care. This population is likely to have restricted access to their smartphone.

2.2 Materials

2.2.1 Demographics Questionnaire. Age, gender, education level, sexual orientation, parent education level as indicator of socioeconomic status, ethnicity, their history of psychiatric disorders, their family history of psychiatric disorders, and recruitment site were measured at baseline (i.e., social media, word of mouth, clinician, poster, Kijiji).

2.2.2 Screen for Child Anxiety Related Emotional Disorders. SCARED is a screening tool for anxiety disorders specifically for use in the youth population (Birmaher et al., 1997) (See Appendix D). It was used to screen for disorders such as general anxiety, separation anxiety, social phobia, and school phobia over the past three months. Separation anxiety questions were excluded as they are designed for younger populations; therefore, the study used 33 out of 38 total questions from the SCARED tool. SCARED asks participants how true they feel each statement is to them based on their last three months. For example, "I worry about other people liking me." The participant can answer "Not true or hardly ever true.", "Somewhat true or sometimes true.", "Very true or often true.", or "Prefer not to answer."

In a study on outpatient youth ages 9-18 years old, the SCARED is found to have good internal consistency a= 0.74-0.93 (Birmaher et al., 1997). In the same study, participants were tested and retested 4 days to 15 weeks later, test-retest reliability was good as determined by intraclass correlation coefficients (0.70-0.90). The SCARED has also generated good discriminative validity between anxiety and other psychiatric disorders such as depression ($r = 0.20$ to 0.47, $p < .001$).

2.2.3 Center for Epidemiologic Studies Depression Scale. Originally created by Radloff (1977), the CES-DC was used to screen for symptoms of depression over the past three months in the present study (See Appendix E). CES-DC consists of 20 questions to measure sadness, loss of interest, appetite, sleep, concentration, guilt, fatigue, agitation, and suicidal thoughts. CES-DC asked participants how often they have experienced symptoms of depression in the past three months. For example, "I did not feel like eating, I wasn't very hungry." The participant can answer: "Not at all", "A little", "Some", and "A lot". Participants also have the choice to select "Prefer not to answer." The cumulative points from 20 questions are used to classify the participant's symptoms.

The CES-DC has been tested to screen for child and adolescent depression (Faulstich et al., 1986; Roberts et al.,1991). It is found to have very good internal consistency ($r=0.84$) Faulstich et al., 1986). CES-DC was found to have adequate re-test reliability of $r= 0.5$ over a period of two-weeks (Faulstich et al., 1986). In terms of validity, CES-DC had a good ability to detect major depression, sensitivity, the true positive rate, was found to be 85% (Garrison et al., 1991). Overall, the CES-DC scale was selected for the current study as it provides an efficient screener for depression that is well validated against highly rated scales and across different ethnicities (Aebi et al., 2009; Dierker et al., 2001; Garrison et al.,1991).

2.2.4 Current Symptoms Self-Report Form Measure of Diagnostic and Statistical Manual of Mental Disorders (DSM-5) Attention-Deficit/Hyperactivity Disorder. The Attention-Deficit/Hyperactivity Disorder Self-Report (ADHD-SR) with adolescent prompts was used to measure comorbid symptoms of ADHD in participants (see Appendix F). Symptoms have been taken from the DSM-5 (American Psychiatric Association, 2013). Participants were asked to answer each question based on their behaviour in the past three months. For example, "I fidget with hands or feet or squirm in my seat." The participant can answer "Never or Rarely", "Sometimes", "Often", "Very Often", or "Prefer not to answer." The ADHD-SR has demonstrated good internal consistency (alpha=0.80) and reliability (alpha=0.79) in an adolescent community sample (Green et al., 2019).

2.2.5 The PROSIT Smartphone Application. The study served as a pilot study for a new mobile sensing application called the Predicting Risk and Outcomes of Social InTeractions (PROSIT) Application. The PROSIT application has been programmed for both Android and iOS operating systems to capture multiple behavioural areas of youth. Having the iOS version of the application gives our research an advantage, as most current mobile sensing applications are limited to Android platforms. It was of particular importance for the team to develop an iOS version of the application because up to 60% of Canada's youth have an iPhone (Afilias Technologies Limited, 2019). The iOS version of the PROSIT application was built in the Swift language using XCode, and the Android version was built using Java, Kotlin languages using

Android Studio. The PROSIT application was not distributed through the official mobile app stores from Apple and Google, it was available to iOS participants through the TestFlight Beta testing application offered by Apple. The Android version of the application was available through a downloadable package sent via email.

The PROSIT application has the potential to measure PA and daily routines using GPS, accelerometer, gyroscope, and magnetometer. It also measures social interactions and mood using music, app use, typing, calling, and texting. Sleep can be measured using ambient light and sound data. The application also has the ability to collect voice samples for analysis. Several other features as also possible with the PROSIT application (See Appendix G for additional information). In the current study the application was used to specifically collect physical activity using the GPS sensor. The data was collected passively in the background of participant smartphones. The GPS sensor was used to determine number of locations visited, distance traveled, and time at home.

Privacy was of utmost importance to protect youth and patients (See Appendix H for additional information on privacy). At the suggestion of the IWK ethics board, GPS location was collected as a general 20-meter location to ensure participant home addresses and specific locations would be protected. All data collected on the phone was anonymized by cryptographic hash functions. The data was stored locally on the smartphone of the participant and automatically uploaded to secure remote servers when the phone was idle and connected to Wi-Fi.

Another important step in designing the PROSIT application was prioritizing phone use impact. The PROSIT application must be constantly running in the background of the smartphone. To limit the impact of the PROSIT tool on the youth's daily phone usage experience, the application has been configured as lightweight as possible, taking up 30 MB of random-access memory. Running the application to collect GPS sensor data can have a large impact on the battery life of a phone, to combat this, data uploads only happened when the device was connected to the WiFi. The PROSIT application would attempt to upload data to the server every hour if connected to WiFi. The app did not use personal data plans to upload data unless approved by the participants. Current testing on a range of smartphones indicated that the tool consumes approximately 20% of the battery over a 24-hour period, and the team is working to improve this in subsequent versions.

2.3 Procedure

The study was approved by the Research Ethics Board of the IWK Health Centre. Prior to beginning the study, all participants completed an online screening and consent process through a secure platform called "REDCap." Consent included control questions to ensure informed consent. Under the guidance of the IWK Health Center ethics board participants ages 10-14, were required to provide additional consent from their parents. Consent from participants aged 15-21 was considered sufficient. Youth and their parents were able to email or call the PROSIT team with any questions. When the consent process was complete, a study ID was assigned to each participant. From this point on, clinical and phone data were only identified by the participants study ID.

There were two study time points, the baseline, and a three-month follow-up (see Table 1). The first time point included a mental health assessment and 14 days of application data collection. The 14-day period was chosen to pilot the use of the application. The length of this period can provide some insight into PA behaviors based on its use in previous exploratory studies in adult populations (Gong et al., 2019). Across a two-week period, a reliable average of PA behaviors can be estimated.. The second time point included a mental health assessment only. The mental health assessment was sent to participants via email. The assessment was completed through a secure link to the REDCap platform. Following baseline assessment, participants were asked to download and set-up the PROSIT application and were provided with login credentials (See Appendix I for participant PROSIT applications instructions). Set-up included allowing the application permission to collect data on their mobile device, for example, access to location data, "Allow PROSIT to access your location while using the app?". Following two weeks of data collection with the application, participants were notified to log-out and/or uninstall the PROSIT application from their smartphone. Participants were be compensated $20.00 CAD gift card for each time-point completed. Participants could withdraw from the study at any time-point and still receive compensation for time-point completed.

2.4 Mobile Sensing Data Extraction

2.4.1 Locations. Raw GPS data was extracted from the mobile sensing data. Data was in the form of latitude and longitude coordinates. Location data was filtered to include unique locations which were defined as a location that was at least 20 meters from the previous data point, and a location in which the participant spent at least two minutes visiting. In the field of mobile sensing there are no standardized techniques for processing smartphone data, therefore the metrics chosen based on previous research and ethical guidelines (Aung et al., 2017). Previous studies have used 30 meters, and 50-meter radiuses, and five-minute durations for location data (Chow et al., 2017; Saeb et al., 2017). A 20-meter location radius, and two-minute duration was based on ethical recommendations; and the aim of obtaining the most precise GPS location data was used while maintaining privacy. The distance between the GPS coordinates was calculated using the haversine formula (distance between two longitude and latitude points on a sphere).

Time stamps of each location were subtracted from one another to determine the time difference between each location. The unique location data was used to aggregate the number of locations visited per day for each participant.

2.4.2 Distance. Distance per day was determined using the sum of the haversine distance between all locations. To extract only walking and running data (not driving), speed between locations was calculated by dividing distance by time. Data points exceeding 13km/h in speed were removed from the data. Further classification of activities based on speed was not completed. Distance per day was aggregated for each participant.

2.4.3 Time at Home. Time at home was defined as the mode of locations visited across all days by each participant. Mode of locations has been used in previous research to determine home location (Boukhechba et al., 2018; Canzian et al., 2015). Mode of locations was used based on previous research that utilized a similar technique Boukhechba et al., 2018; Canzian et al., 2015). Once the home location was determined, the sum of time spent within 20 meters of this location was calculated per day for each participant. Time at home was considered a proxy of sedentary behaviour.

2.5 Statistical Analysis

2.5.1 Missing Values and Outliers. 161 participants downloaded the application, 122 completed the two weeks of GPS data collection. The data was cleaned to remove 10/122 (8.20%) participants due to data error, including participants that had no locations 20 meters apart or impossible data points likely due to phone privacy settings. 10/122 (8.20%) participants were missing mental health assessment data at baseline (4 missing anxiety sum scores, 7 missing depression sum scores). There were 11/112 (9.82%) participants that did not fully complete the 3-month follow-up assessment for anxiety and/or depression. In total at baseline there were 112 participants in the study, and 101 participants at follow-up. The number of participants included in each analysis and model varied as different numbers of participants had missing data on different variables. Independent t-tests were run to determine if there were differences in gender, SES, age, diagnosis, baseline mental health assessment scores, and the month participants joined the study, these variables were not associated with missing data. There were no statistically significant differences found between samples, therefore the data was missing at random. Manipulation of missing data was not employed because testing hypothesis two included outcome data from only one time point, additionally, the reason data was missing for predictor variables is unrelated to anxiety and depression symptoms, it is due to data collection error. Therefore, using a complete case analysis would have negligible bias (Allison, 2000; Sterne et al., 2009; Steyerberg & Veen, 2007). Further, manipulation of missing data was not used for testing of hypothesis three because there was <10% loss at follow-up which can be considered minimal (Bennet, 2001; Dong & Peng, 2013;). Overall, the present pilot study aims to limit bias to understand the relationship of PA and mental health.

Prior to correlations and statistical models, an outliers analysis was completed. For GPS data, which was not normally distributed, the Hampel filter method was employed (Enderlein, 1987). This consisted of removing values outside the interval formed by the median, plus or minus 3 median absolute deviations. Based on this method, there were five distance per day means removed. In addition, eight locations per day means removed. Finally, there were six time at home per day means removed. Dependent variables were normally distributed therefore outliers more than 1.5 interquartile range below quartile 1 or above quartile 3 were removed (Sciffler, 1988). There were no outliers for sum depression and anxiety scores, one outlier for change in anxiety scores, and two for change in depression scores.

The outliers were removed due to the high chance of measurement error, especially while using the mobile sensing application. The analysis was run with and without outliers, the outliers impacted the results, prior to the removal of outliers some findings were significant and became not statically significant after the removal. The chance of error is due to the application being newly developed and piloted throughout the study, therefore there were software bugs and crashes, and phone compatibility issues (older phone models). In addition, errors could occur due to misinterpretation of data (e.g., driving in traffic classified as walking). This aligns with other studies that excluded 12.5% of sample due to software bugs and compatibility issues (Chow et al., 2017). Specifically for GPS data, Saeb at al., (2016) excluded 45% of their participants in their analysis due to issues with the sensor and missingness.

2.5.2 Descriptive Statistics. As described above, mean locations per day, distanced traveled per day, and time at home per day were calculated for each individual participant. The sum score for mental health assessment data was extracted (SCARED, CES-DC, ADHD-SR). Descriptive statistics were explored for all variables. Covariates were determined based on previous literature as well as their association with anxiety and depression in the current data set. The study wanted to compare the fit of models with and without passively collected data, to ensure practicability, the focus was on covariates that are data commonly associated with the development of psychiatric disorders. Covariate data included demographic data, age, gender, mother's education as an indicator of SES (Chaplin et al., 2009; Hankin et al., 1998; Lemstra et al., 2008). Comorbidities ADHD, depression, anxiety (Garber & Weersing, 2010); Xia et al., 2015). The month participants joined the study to account for COVID-19, and phone type (iPhone or Android) (Benenson et al., 2013; Götz et al., 2017).

Further, Spearman's correlations were run on mean PA data and the SCARED and CES-DC scores. Spearman's correlation was used due to data having a non-normal distribution. All correlations were adjusted for age, gender, smartphone's operating system (iOS or Android), and maternal education as an indicator of socioeconomic status. As well, the month of baseline assessment was controlled for to account for potential impacts of the COVID-19 pandemic on results.

2.5.2 Addressing Study Aims. To address hypothesis one and analyze the feasibility and acceptability of the mobile sensing application in youth, the study looked at participant descriptive characteristics to better understand if they were able to successfully recruit youth with anxiety and depression. Furthermore, the dropout rate was analyzed to determine if using the application for 14-days was feasible for youth. The reasons for drop out were collected and counted through email to understand how many participants dropped out due to privacy concerns with the application.

For hypothesis testing the alpha level was 0.05. The F-test was used for the overall significance test, and the t-test was used for the individual significance test. As the F-test checks, all the predictors simultaneously there is protection against multiple comparisons. This corresponds to Scheffé's method which uses the F-distribution (Salkind, 2010).

To address hypothesis two, a hierarchical multiple regression model was run in RStudio software, using the 4.1.2 GUI 1.77 Big Sur version of R. To explore if baseline mean distance, locations, and time at home per day can predict unique variance in baseline anxiety (SCARED) and depression (CES-DC) above covariates. R^2 was calculated for the covariate model (gender, age, socioeconomic status, month they joined the study, phone type, comorbidities). Based a study of PA and mobile sensing in youth, distance was added into the model first (Cao et al., 2020). The present study estimated distanced travelled on foot, making it comparable to daily steps. In the study by Cao et al (2020), daily steps measured by a smartphone were found to have a moderate positive correlation with depression and anxiety in youth, and a small correlation for number of locations visited. The PA variables of locations visited and time at home were each entered into the regression model with distance to test if they improved the model fit. There was no intention of excluding any variables from the full regression model throughout this process, therefore the results were not impacted by the order of variables entered into the model. The full regression model was run to explore if PA at baseline (mean distance, locations, and time at home per day) can predict unique variance in baseline anxiety (SCARED) and depression (CES-DC). R^2 was calculated for the baseline model (gender, age, socioeconomic status, month they joined the study, phone type, comorbidities), and compared to the full model which included all PA predictor variables. ANOVAs were run to compare models to determine if PA variables were able to provide a statically significant increase in R^2. ANOVAs were run to compare models to determine if PA variables were able to provide a statically significant increase in R^2.

To address hypothesis three, a multiple regression model with a change score was selected to analyze the data. The author opted to use a change score because the longitudinal data only included measurement of the outcome variables at two times points. The predictor variables (PA) were only measured at one time point, making a multiple regression with a change score the simplest way to analyse the data. It is noted that a mixed model could be helpful in the future, especially for studies that include additional measurements of symptoms or additional time points of PA data.

The changes in symptoms over time was calculated by subtracting baseline sum scores from three-month follow-up sum scores on the SCARED and CES-DC questionnaires for each participant. Those that did not complete the follow-up questionnaire or had missing data were excluded. Based on research investigating the impact of stay-at-home orders during COVID-19, time at home was predicted to have the largest impact on mental health longitudinally, therefore it was added to the baseline model first (Giuntella et al., 202; Marroquín et al., 2020;). Distance and location per day were subsequently added to the model with time at home to see if they improved the model fit. There was no intention of removing any variables from the final regression model throughout this process therefore the results were not impacted by the order of variables entered into the model. The full regression model was run to explore if PA at baseline (mean distance, locations, and time at home per day) can predict unique variance in the total change in scores (delta y) on the scale for anxiety (SCARED) and depression (CES-DC). R^2 was calculated for the baseline model (gender, age, socioeconomic status, timepoint during pandemic, phone type, comorbidities), and compared to the full model which included all PA predictor variables. ANOVAs were run to compare models to determine if PA variables were able to provide a statically significant increase in R^2.

CHAPTER 3 RESULTS

3.1 Feasibility

It was hypothesized that youth with and without a psychiatric disorder would be able download a mobile sensing application and complete 14-days of data collection. There were 161 participants that downloaded the PROSIT application. 25/161 (15.53%) of the participants did not provide two weeks of data. 3/161 (1.86%) of the participants did not provide GPS sensor data. There were 11/161 (6.83%) study withdraws. In sum, 122 (76%) completed the two weeks of GPS data collection. The hypothesis was supported, there were 122 youth participants, with and without psychiatric disorders, that were able to successfully complete 14-days of data collection. It was also hypothesized participants would report minimal issues and privacy concerns with the application, the hypothesis was supported, out of 11 study withdraws, only three (1.86%) were due to privacy.

Participant descriptive statistics were calculated after data cleaning, which removed 10/122 (8.20%) participants that had GPS data with errors. Participants ranged from age 10-21, with a mean age of 18.04 years old (SD = 2.82), and 96 of the participants were female (85.71%). Additional sample descriptives can be found in Table 2 and Table 3. Means and correlations of predictors and outcome variables of interest were calculated after the removal of outliers and can be found in Table 4 and Table 5.

3.2 Depression and Anxiety at Baseline

It was hypothesized that baseline PA data (mean daily time at home, distance traveled, and number of locations visited per day) would explain unique variance in self-reported anxiety (SCARED) and depression (CES-D) at baseline, over and above demographic (gender, age, socioeconomic status) and control variables alone (timepoint during pandemic, phone type, comorbidities). Two hierarchical multiple regression models were run, the first to determine if the addition of PA data improved the fit of the model for anxiety, and the second for depression.

Both hierarchical multiple regression models met the assumptions. There was linearity as assessed by partial regression plots and a plot of studentized residuals against the predicted values. There was independence of residuals, as assessed by a Durbin-Watson statistic. There was homoscedasticity, as assessed by visual inspection of a plot of studentized residuals versus unstandardized predicted values. There was no evidence of multicollinearity, as assessed by tolerance values greater than 0.1, and Variance Inflation Factor (VIF) less than 5 (Ringle et al., 2015). There were no studentized deleted residuals greater than ±3 standard deviations, and values for Cook's distance above 1. There assumption of normality was met, as assessed by Q-Q Plot.

3.2.1 Anxiety. The addition of mean distance per day to the baseline model predicting anxiety (Model 2) lead to an increase in R^2 adjusted of 0.002, which was not statistically significant $F(1, 87)= 1.49$, $p = .23$ (Table 6). For model 3, the addition of mean locations per day to Model 2 lead to a decrease in R^2 adjusted of 0.005, which was not statistically significant $F(1, 79)= .07$, $p=0.80$. For model 4, the addition of mean time at home per day to Model 2 lead to a decrease in R^2 adjusted of 0.002, which was not statistically significant $F(1, 80)=0.63$, $p=.43$.

A model including all covariates, i.e., ADHD, depression, education of mother, gender, age, phone type, timepoint during pandemic, mean locations per day, and mean distance per day, mean time at home to predict anxiety was statistically significant R^2 adjusted = 0.63, $F(10, 73)= 14.74$, $p<0.0001$. In the full model, adding PA variables did not improve the model fit, no unique variance in self-reported anxiety was explained above and beyond covariates, $F(3, 73)= .63$, $p=0.66$, therefore the hypothesis was not supported.

3.2.2 Depression. The addition of mean distance per day to the baseline model predicting depression (Model 2) lead to an increase in R^2 adjusted of 0.01, which was not statistically significant $F(1, 87)= 2.60$, $p = .11$ (Table 7). For model 3, the addition of mean locations per day to Model 2 lead to a decrease in R^2 adjusted of 0.01, which was not statistically significant $F(1, 79)= 0.02$, $p=0.89$. For model 4, the addition of mean time at home per day to Model 2 lead to a decrease in R^2 adjusted of 0.003, which was not statistically significant $F(1, 80)=.18$, $p=.68$.

A model including all covariates, i.e., ADHD, anxiety, education of mother, gender, age, phone type, timepoint during pandemic, mean locations per day, and mean distance per day, mean time at home to predict depression was statistically significant R^2 adjusted = 0.64, $F(10, 73)= 15.68$, $p<0.0001$. In the full model, adding PA variables to did not improve the model fit, no unique variance in self-reported depression was explained above and beyond covariates, $F(3, 73)= .21$ $p=0.89$, therefore the hypothesis was not supported.

3.3 Change in Anxiety and Depression from Baseline to Follow-up

It was hypothesized that baseline PA data (mean daily time at home, distance traveled, and number of locations visited) would predict unique variance in the total change in scores (Delta Y) on the scale for anxiety (SCARED) and depression (CES-DC) from baseline to three-month follow-up, over and above demographic (gender, age, socioeconomic status) and control variables alone (timepoint during pandemic, phone type, comorbidities). Two hierarchical multiple regression models were run, the first to determine if the addition of PA data improved the fit of the model for anxiety, and the second for depression.

Both hierarchical multiple regression models met the assumptions. There was linearity as assessed by partial regression plots and a plot of studentized residuals against the predicted values. There was independence of residuals, as assessed by a Durbin-Watson statistic. There was homoscedasticity, as assessed by visual inspection of a plot of studentized residuals versus unstandardized predicted values. There was no evidence of multicollinearity, as assessed by tolerance values greater than 0.1, and Variance Inflation Factor (VIF) less than 5 (Ringle et al., 2015). There were no studentized deleted residuals greater than ±3 standard deviations, and values for Cook's distance above 1. There assumption of normality was met, as assessed by Q-Q Plot.

3.3.1 Anxiety. The addition of mean time at home per day to the baseline model understanding change in anxiety. Displayed in Model 2, time at home lead to an increase in R^2 adjusted of 0.13, which was statistically significant $F(1, 71)= 11.291$, $p = <0.001$ (Table 8). For model 3, the addition of mean distance per day to Model 2 lead to a decrease in R^2 adjusted of 0.01, which was not statistically significant $F(1, 65)=0.26$, $p=.61$. For model 2, the addition of mean locations per day to Model 2 lead to a decrease in R^2 adjusted of 0.001, which was not statistically significant $F(1, 62)= 0.90$, $p=0.35$.

A model including all covariates, i.e., ADHD, follow-up depression, education of mother, gender, age, phone type, timepoint during pandemic, mean time at home, mean locations per day, and mean distance per day, to predict the change in anxiety was statistically significant R^2 adjusted = 0.15, $F(10, 58)= 2.22$, $p=0.03$. In the full model, adding PA variables improved the model fit, unique variance in self-reported anxiety change was explained above and beyond covariates, $F(3, 58)= 4.22$, $p=0.01$, therefore the hypothesis was supported. Cohen's f^2 for the addition of all three PA variables to the model is 0.20, indicating a medium effect size (Cohen, 1988). Standardized Beta coefficients were as follows; mean time at home per day (.40, *CI* .16-.64), mean locations per day (-.20, CI -*.50*-.11), mean distance traveled per day (.15, *CI* -.17-.46).

3.3.2 Depression. The addition of time at home per day to the baseline model predicting depression (Model 2) lead to an increase in R^2 adjusted of 0.04, which was not statistically significant $F(1, 70)= 3.79$, $p = .06$ (Table 9). For model 3, the addition of mean locations per day to Model 2 lead to an increase in R^2 adjusted of 0.02, which was not statistically significant $F(1, 62)=2.91$, $p=.09$. For model 4, the addition of mean distance per day to Model 2 lead to a decrease in R^2 adjusted of 0.03, which was not statistically significant $F(1, 64)= 3.20$, $p=0.08$.

A model including all covariates, i.e., ADHD, anxiety, education of mother, gender, age, phone type, and month of assessment, mean locations per day, and mean distance per day, mean time at home to predict the change in depression was not statistically significant R^2 adjusted = 0.06, $F(10, 58)= 1.51$, $p=0.16$. In the full model, adding PA variables improved the model fit, unique variance in self-reported changes in depression was explained above and beyond covariates, $F(3, 58)= 2.96$ $p=0.04$, therefore the hypothesis was supported. Cohen's f^2 for the addition of all three PA variables to the model is 0.07, indicating a small effect size (Cohen, 1988). Standardized Beta coefficients were as follows; mean time at home per day (.25, *CI* 0-.50), mean locations per day (-0.15, *CI* -.47-.16), mean distance traveled per day (-.15, *CI* -.48-.16).

CHAPTER 4 DISCUSSION

4.1 Feasibility of Mobile Sensing in Youth

The study aimed to, firstly, pilot and assess feasibility of a mobile sensing application in youth participants with iOS and Android devices. Secondly, to determine if smartphone-based PA data can explain unique variation in depression and anxiety scores, and changes in scores over time. It was first hypothesized that youth with and without psychiatric disorders would be able download a mobile sensing app and complete 14-days of data collection. Additionally, participants were expected to report minimal issues and privacy concerns with the application. The first hypothesis was supported, the study was able demonstrate that the use of a mobile sensing applications is feasible in youth with and without disorders. Prior to beginning this study, the only published mobile sensing study on youth included 11 participants (Cao et al., 2020). The current study included over 100 youth, and participants as young as age 10. Therefore, expanding the literature and indicating mobile sensing applications can be used successfully by young users. This aligns with the idea that youth are ideal candidates for mobile sensing data collection because they are active smartphone users, with a strong attachment to their phones (Ventä et al., 2008).

Consistent with the first hypotheses, there was reporting of minimal privacy concerns as the reason for drop out or withdraw. Participants with psychiatric disorders were not more likely to drop out of the study, and 75% of participants were able complete the two weeks of data collection. This finding is consistent with previous research, patients with severe psychiatric disorders have been successfully involved in mobile sensing studies (Ben-Zeev et al., 2016). For example, patients diagnosed with schizophrenia have engaged in mobile sensing research.

Additionally, The PROSIT application was used by participants with both Androids and iOS smartphones. Designing an application for use with each software was critical to the research team. Majority of mobile sensing studies have only been available to participants with Android devices, with a couple of studies encompassing iOS software (Boukhechba et al., 2018; Gong et al., 2019). The popularity of iOS devices among participants was high and represented 85.71% of the sample. In majority of previous studies these participants would have been excluded due to device type.

4.2 Anxiety and Depression at Baseline

Secondly, it was hypothesized that baseline PA data would predict unique variance in baseline anxiety and depression symptoms, over and above control variables alone. Adding GPS mobile sensing data to regression models did not help explain anxiety symptoms, therefore the hypothesis for baseline anxiety was not supported. Based on the results, mobile sensing PA data is not a good measure of anxiety symptoms, PA explained very little variance in the models. These findings are similar to a recent study in youth, Cao et al., (2020) were unable to demonstrate a statistically significant correlation between locations per day and anxiety symptoms. The current study used a measure of generalized anxiety, in adults, there is lack of research on generalized anxiety disorder and smartphone GPS data, with majority of research focusing on social anxiety specifically (Boukhechba et al., 2018; Chow et al., 2017). In one study, generalized anxiety symptoms were found to not be correlated with time at home, which aligns with the finding of the baseline anxiety model in the current study (Saeb et al., 2017). On the contrary in social anxiety, previous literature was able to predict social anxiety levels with an 85% accuracy rate using GPS location data, those high in social anxiety were found to be more likely to avoid public places and go out less (Boukhechba et al., 2018; Chow et al., 2017). The current study had very few participants with social anxiety (<11%), therefore the focus remained on generalized anxiety, and aligns with results on such.

Similar to anxiety, adding GPS mobile sensing data to regression models did not help explain self-reported depression symptoms. The hypothesis was not supported, mobile sensing PA data did not provide a good measure of depression symptoms. The findings did not support previous research which found depression symptoms in youth to be associated with lower mobility and visitng of fewer locations. Additionally, the findings did not replicate previous research in adults that found a correlation between high depression symptoms and less PA (Canzian et al., 2015).

Overall, it appears that GPS mobile sensing data alone was not enough to explain variance in baseline anxiety and depression symptoms in this sample of youth. This finding could be because the pandemic impacted the natural variability in PA. Research has shown COVID-19 to cause reductions in movement patterns which could limit GPS data as a predictive tool (Giuntella et al., 2021). Another explanation for the null finding could be that PA only represents one of many ways symptoms of anxiety and depression can manifest as behaviors. Based on previous literature, sleep, and social behaviors could aid prediction models of anxiety and depression (Jongs et al., 2020). More detail about youth's behaviour and daily routines is needed to understand the well-being of youth at one given time point. The addition of these measures can be used to create a more well-rounded behavioral profile. PA can be expanded upon; additional sensors in mobile phones can be used to track PA, including accelerometer, gyroscope, magnetometer (Rohani et al., 2018). These sensors may provide further detail and insight into PA data. Mobile sensing provides a measure of social interactions through call and texting logs to determine how youth socialize (Eskes et al., 2016; Rohani et al., 2018;). For example, how many calls and texts they send, and how many contacts they socialize with. Mobile sensing technology can also offer a new accurate measure of sleep. Previous research shows that sleep measured using a smartphone is potentially more accurate of sleep onset than actigraphy (Borger et al., 2019). The addition of social behaviors and sleep could improve the fit of models.

4.3 Anxiety and Depression from Baseline to Follow-up

Thirdly, it was hypothesized that baseline PA data will predict unique variance in the total change in scores on the scale for anxiety (SCARED) and depression (CES-DC), from baseline to three-month follow-up, over and above demographic and control variables alone. Adding GPS mobile sensing data to regression models helped predict the change in anxiety and depression symptoms from baseline to follow-up, therefore the hypothesis was supported. Mobile sensing PA data variables had a small to medium effect on the prediction of future anxiety and depression symptoms. Use of PA in models predicting future symptoms in youth could be helpful, and likely aid other prediction models (Jongs et al., 2020). Remaining in the state of low or high PA, especially during the COVID-19 pandemic, could have an effect on future mental health. Although, the study only consisted of a 14-day mobile sensing data collection period, therefore we cannot determine the consistency of PA levels over the three-month gap between mental health assessments. To further understand how PA levels predict anxiety and depression, future research could include studies with longer periods of mobile sensing data collection, along with more frequent mental health assessments (For example, Faurholt-Jepsen et al., 2019).

In the previous analysis of anxiety and depression at baseline, PA data was not valuable for predicting symptoms that were measured concurrently with PA data collection. Also known as prediction of mental health “state.” Majority of studies have focused on detecting mental health “states,” with very few studies looking at mobile sensing behaviours that predict future symptoms, as done in the current analysis (Meyerhoff et al, 2021). The authors are only aware of two studies in adults, firstly, there is a study on 18 patients with bipolar disorder that was able to predict future depression symptom severity using smartphone typing rates (Strange et al., 2018). Secondly, a study by Meyerhoff et al. (2021) did predict future symptoms using GPS data but did not claim a causal relationship between PA and depressive symptoms, however, they did find that changes in GPS data (specifically location data) preceded changes in depressive symptoms. The study did not find changes in depressive symptoms to precede behaviour changes. Our study also looked at if GPS data can predict future symptoms but did not look at changes in GPS data over time. The present study was the first to look at if GPS mobile sensing data (PA) can explain changes in anxiety and depression in youth. The pilot study results are promising but as previously discussed, warrant future longitudinal research to understand how GPS data can predict future depression and anxiety symptoms in youth.

4.4 Clinical Significance

The study investigated mobile sensing in youth, as it has the potential to provide a secondary prevention measure by being a clinical monitoring tool. When used as a monitoring tool, mobile sensing can offer insight into the changes of behaviour and symptoms in youth that go undetected between appointments (Cao et al., 2020). Detecting these changes could be crucial because there is a need for effective early intervention in youth with psychiatric disorders (Comeau et al., 2019; Georgiades et al., 2019). For youth currently not in treatment for a psychiatric disorder, there is the potential for mobile sensing to provide remote intervention (through personalised feedback) or encourage healthy behaviours that can reduce the chance of developing a psychiatric disorder (Aung et al., 2017). A similar remote approach has been used to encourage healthy behaviours in commercial devices such as Ubifit, BeWell, and the Apple Watch. Personalized feedback on devices is provided through graphics for self-reflection. Mobile sensing could provide an affordable, wide scale approach to help close the treatment gap and globally reduce the burden of psychiatric disorders (Frankish et al., 2018; Georgiades et al., 2019 Hintzpeter et al., 2015; Kessler et al., 2007; Vos et al., 2017).

Considering the COVID-19 pandemic, there is additional emphasis on developing clinical monitoring tools that can identify poor mental health. Such tools can provide a way for youth to self-monitor their behaviors, which can be vital to reduce the burden of future catastrophes, a time when the treatment gap is further exacerbated (Huckins et al., 2020, Griffin & Saunders et al., 2019). Recent research has shown that a large percentage of people rated mobile sensing applications as very helpful for managing their mental health during the COVID-19 pandemic (Suruliraj et al., 2021). As well, those with a previous history of a mental disorder found mobile sensing applications especially helpful, they provided awareness of maladaptive behaviours such as increased sedentary time or screen time. The current study demonstrates the collection of mobile sensing PA data, which could be useful for interventions targeting behaviour change. For example, in behavioural activation therapy, the goal for the patient may be to increase physical activity, or time in nature. Behavioural activation can be an effective treatment for depression in young people, with the potential to be monitored by mobile sensing but further research is needed to establish effective use (Tindall et al., 2017).

Despite the appealing nature of mobile sensing in youth, research on mobile sensing is preliminary (Cao et al., 2020). Further groundwork is needed to tailor the use of mobile sensing in clinical contexts, including the use of personalized health tips and interventions derived from smartphone data (Aung et al., 2017; Boukhechba et al., 2020; Cornet & Holden 2018, Hilty et al., 2020; Torous et al., 2021; Wisniewski & Torous, 2020;). Studies in adult clinical populations have successfully applied a real-world approach (Grünerbl et al., 2015). Yet, one outstanding issue to reaching widespread use of mobile sensing in clinical care is that there is currently no standardized way to process raw data from smartphones (Aung et al., 2017). There is a need for replication and more rigorous methodology to produce a widely used clinical monitoring tool with mobile sensing technology (Melbye et al., 2020). In addition, caution must be taken, a recent randomized controlled trial on mobile sensing in adults with bipolar disorder found that patients in the mobile sensing group were more likely to experience depressive symptoms (Faurholt-Jepsen et al., 2020). Despite the study also reporting the improved quality of life and reduced perceived stress for the mobile sensing intervention group, it is suggested that continuous monitoring of depressive behaviors could have a harmful effect. Therefore, before health tips or patient feedback is employed research must continue to investigate the effects of smartphone monitoring.

4.5 Limitations and Future Directions

This research was able to expand on a previous study that included only 11 youth participants, with a sample of 122. The sample is still considered modest for mobile sensing research, larger samples would allow for the power to investigate moderating variables and develop effective machine learning models. With the additional extraction of missing data and measurement error the sample was reduced to between 69 and 96 participants depending on the analysis, this subsequently reduced statistical power. Approximately 50-65% of power was retained. The study was therefore limited by this reduction in power, possibly resulting in null findings, an expanded sample size is needed to confirm results via replication. This was not completely unexpected as the study acted as a pilot study for the PROSIT application, therefore the new application was still in the beta testing stage. Application and server crashes were common which may have impacted the quality of the data. With further updates to ensure stability of the application, these concerns and crashes should decrease. The application development team has been working rapidly to improve it for future use. In addition, for the application to passively collect data, it must be left open in the background of the phone. The participants manually closing the app (swiping up) created periods of time without data. The research team worked diligently to consistently remind participants to re-open the application and resume data collection. Informing participants to keep the application open in the background of the smartphone is highly recommended.

The study also included limitations with regards to its lack of context in PA behaviours. The context of behaviors can be dependent on the population and sample, making it hard to generalize behaviour differences (Müller et al., 2021). As well, without context of behaviours the study is not able to make claims regarding the causation of depression and anxiety from PA. Most importantly, the data was collected in the context of the COVID-19 pandemic, the pandemic reduced the natural variance in PA levels, which made predictions more difficult. The results may not apply to behaviour post-pandemic. Behaviour and responses to the COVID-19 pandemic may be influenced by fear and government restrictions (Mantica et al., 2020; Ornell et al., 2020; Mantica et al., 2020; Zheng et al., 2021). Behaviour changes during the pandemic included decreased PA, in person health care, emergency room visits, sleep, social visits, and travel (Desborough et al., 2020; Giuntella et al., 2021; Mantica et al., 2020; Zheng et al., 2021). Further reiterating that the study is limited by the changes of PA during the COVID-19 pandemic.

To provide additional context, future research should include indication of home location by participants. The current study used the most frequented GPS coordinates (and data points within 20 meters) as the participants home location. The most frequented location may have not provided the correct home location. If participants had divorced parents or spent a large amount of time at friend's house (sleepovers etc.), the home location may have been inaccurate. It is recommended that future studies have participants indicate their home location on the application. Although the current study did not have ethical approval to detect exact home location, previous studies have used user-based information to determine locations (Saeb et al., 2017). Participants code GPS locations with the type of locations they are visiting (home, work, school etc.), this helped to better understand the relationship of GPS data and mental health.

In addition to improving the mobile sensing application, future research should investigate application validation against actigraphy wrist watches to understand if mobile sensing is a good measure of PA levels. A wristwatch could incorporate heartrate data to determine intensity of PA, which can be an important component for understanding negative mental health symptoms (Hrafnkelsdottir et al. 2018) Wrist worn actigraphy has been shown to be a good measure of PA levels in youth (Colley et al., 2012). Without validation of the application, it is especially acknowledged that mobile sensing may not capture all PA, for example swimming or organized sports. This limitation should be kept in mind when collecting mobile sensing PA data for mental health care.

The inconsistency of results between the two types of analysis, detecting state anxiety and depression and predicting future symptoms could also suggest that a within subject analysis may provide a better model. Previous literature discusses the complexity of human behaviour, and that in many cases individualized models may be more fitting as they allow for a more flexible approach to symptom prediction (Aung et al., 2017; Breiman, 2000). A systematic review by Cornet & Holden (2018) found that seven studies concluded individualized models were better for predicting participants health and well-being in comparison to generalized models. Many people have different behaviour indicators of health, therefore individualized data, or groupings of people with similar behaviour may provide a more helpful monitoring and feedback system for youth (Aung et al., 2017; Cornet & Holden, 2018).

CHAPTER 5 CONCLUSIONS

The acceptability, and feasibility of the PROSIT application provides preliminary information on the use of mobile sensing in youth mental health care. The study successfully piloted an application for both Android and iOS smartphones and demonstrated the potential for mobile sensing to help predict future mental health symptoms. Although, monitoring PA alone was not enough to consistently predict anxiety and depression. Our study reiterates the need for larger studies with rigorous and standardized measures in the field of smartphone mobile sensing. In addition, measurement of multiple health behaviors such as sleep, and social interactions is recommended. By continuing to improve the PROSIT application and study the use of mobile sensing, research can work towards discovering if mobile sensing has a place in youth mental health care.

Table 1. Timeline of study

Time Point	Questionnaires			PROSIT App	Duration
Baseline	SCARED	CES-DC	ADHD-SR	2 weeks recording	35-45 mins
3-month follow up	SCARED	CES-DC	ADHD-SR	N/A	15-20 mins

Table 2. Participant demographics

Ethnicity	N	% of sample
Indigenous	6	5.36
Black Canadian	7	6.25
Caucasian	95	84.82
Mothers Education		
High school	17	15.18
Further education	29	25.89
University	54	48.21
Phone type		
iOS	89	79.46
Android	23	20.53

Note: N=112

Table 3. Mental Health Disorder Lifetime Diagnosis and Treatment Status

Diagnosis	N	% of sample	In treatment	% of sample
Depression diagnosis	37	33.04	12	10.71
Anxiety diagnosis	38	33.93	14	12.50
Social Anxiety Disorder	12	10.71	6	5.36
ADHD diagnosis	10	8.93	6	5.36

Note: N=112

Table 4. Means and standard deviations of main study variables

Variable	M	SD	N
SCARED Baseline	33.89	14.68	108
SCARED Follow-up	34.45	14.10	96
CES-D Baseline	33.71	14.98	105
CES-D Follow-up	31.75	14.85	93
Mean change in CES-D	-2.61	9.65	87
Mean change in SCARED	-.95	7.38	91
Locations Per Day	11.82	6.77	102
Distance Per Day	3.99	2.56	107
Time at Home Per Day	9.47	4.07	106

Note. Time at home is in hours, distance is in kilometers.

Table 5. Spearman's correlations for main study variables with corrections

Variable	1	2	3	4	5
1. Mean distance per day	-				
2. Mean locations per day	**.61****	-			
3. Mean time at home	-.08	-.06	-		
4. Anxiety (SCARED)	.2	.18	-.08	-	
5. Depression (CES-D)	**-.21***	-.16	-.03	**.7****	-

Note. **=statistically significant at p<.05. **=statistically significant at p<.001.*

Table 6. Hierarchical multiple regression predicting anxiety

	Baseline		Model 2		Model 3		Model 4	
Predictors	*B*	*CI*	*B*	*CI*	*B*	*CI*	*B*	*CI*
Gender	-.08	-.22 – .05	-.10	-.24 – .03	-.09	-.24 – .06	**-.14***	-.28 – -.00
Phone	-.08	-.22 – .05	-.11	-.25 – .03	-.08	-.23 – .07	-.09	-.23 – .05
Age	.00	-.14 – .15	.01	-.14 – .15	.03	-.13 – .19	.02	-.12 – .17
Covid	-.04	-.17 – .09	-.01	-.15 – .12	-.05	-.20 – .10	-.06	-.19 – .08
Depression	**.77****	.62 – .92	**.78****	.63 – .93	**.77****	.62 – .92	**.79****	.64 – .94
Mother's education	.04	-.09 – .18	.06	-.08 – .19	.06	-.09– .21	.08	-.06 – .22
ADHD	.05	-.10 – .21	.05	-.10 – 0.21	.07	-.09 – .23	.01	-.14 – .17
Distance			.09	-.06 – .23	.04	-.15 – .23	.04	-.10 – .18
Locations					.02	-.16 – .40		
Time at home							-.06	-.19 – .08
Observations	96		96		89		90	
R^2 / R^2 adjusted	.63 / 0.60		.63 / 0.60		.63 / 0.60		.67 / 0.63	

Note. **p<0.05, ** p<0.01*

Table 7. Hierarchical multiple regression predicting depression

	Baseline		Model 2		Model 3		Model 4	
Predictors	*B*	*CI*	*B*	*CI*	*B*	*CI*	*B*	*CI*
Gender	.03	-.10 – .16	.06	-.08 – .20	.03	-.11 –.17	.06	-.08 – .19
Phone	.03	-.10 – .16	.06	-.08 – .20	.04	-.11 –.19	.04	-.09 – .18
Age	.10	-.04 – .24	.10	-.04 – .23	.05	-.11 – .21	.08	-.06 – .22
Covid	.07	-.05 – .20	.07	-.09 – .17	.11	-.08 – .26	.08	-.05 – .21
Anxiety	**.72****	.58 – .85	**.72****	.58 – .85	**.73****	.58 – .87	**.73****	.59 – .87
Mother's Education	-.06	-.19 – .07	-.07	-.21 – .06	-.09	-.24 – .06	-.09	-.22 – .04
ADHD	**.17***	.03 – .32	**.02***	.02 – .31	.14	-.01 – .29	**.19***	.05 – .33
Distance			-.11	-.25 – .03	-.02	-.20 – 0.16	-.08	-.21 – .06
Locations					-.01	-.19 – .16		
Time at home							-.03	-.16. – .11
Observations	96		96		89		90	
R^2 / R^2 adjusted	.65 / .63		.66 / .63		.65 / .61		.70 / .66	

Note. **p<0.05, ** p<0.01*.

Table 8. Regression predicting change in anxiety from baseline to follow-up

	Baseline		**Model 2**		**Model 3**		**Model 4**	
Predictors	*B*	*CI*	*B*	*CI*	*B*	*CI*	*B*	*CI*
Gender	-.03	-.27 – .21	.02	-.20 – .25	.05	-.20 – .29	.02	-.20 – .25
Phone	.07	-.17 – .31	.04	-.18 – .26	.06	-.19 – .30	.04	-.19 – .28
Age	**-0.31***	-.57 – -.05	**-.40***	-.65 – -.15	**-.39***	-.64 – -.13	**-.37***	-.64 – -.10
Covid	.02	-.21 – .26	.00	-.22 – .22	-.03	-.26 – .20	.00	-.25 – .25
Depression	0.02	-0.26 – 0.30	.09	-.18 – 0.12	.07	-0.21 – .34	-0.03	-.31 – .25
Mother's Education	-.17	-.41 – .08	-0.17	-.40 – .05	-.15	-.39 – .09	-.18	-.42 – .07
ADHD	-.18	-.47 – .11	-.23	-.50 – .04	-.21	-.49 – .07	-.20	-.47 – .08
Time at Home			**.38**	-.16 – .60	**.39**	-.16 – .63	**.37**	.14 – .60
Distance					-.06	-.31 – .18		
Locations							-.11	-.36 – .13
Observations	80		80		75		72	
R^2 / R^2 adjusted	.10/ .01		.23 / .07		.24 / .14		.26 / .15	

Note. *$p<0.05$

Table 9. Regression predicting change in depression from baseline to follow-up

	Baseline		**Model 2**		**Model 3**		**Model 4**	
Predictors	*B*	*CI*	*B*	*CI*	*B*	*CI*	*B*	*CI*
Gender	-.14	-.38 – .10	-.11	-.35 – .13	-.06	-.23 – .23	-.03	-.29 – .22
Phone	.03	-.21 – .26	.03	-.20 – .26	.01	-.32 – .19	.08	-.17 – .32
Age	**-.26***	-.52 – .00	**-.32***	-.58 – -.06	-.20	-.49 – .09	**-.30***	-.57 – -.04
Covid	-.08	-.31 – .15	-.08	-.31 – .14	-.18	-.43 – .07	-.13	-.36 – .11
Anxiety	-.12	-.38 – .15	-.08	-.34 – .19	-.09	-.37 – .19	-.09	-.36 – .17
Mother's Education	-.01	-.24 – .22	-.01	-.24 – .22	-.01	-.25 – .24	-.03	-.27 – 20
ADHD	-.13	-.42 – .15	-.16	-.44 – .13	-.09	-.38 – .20	-.17	-.45 – .11
Time at Home			.22	-.01 – .45	.22	-.03 – .46	.24	-.01 – .48
Locations					-.22	-.47 – .04		
Distance							-.22	-.47 – .08
Observations	79		79		72		74	
R^2 / R^2 adjusted	.12 / .03		.16 / .07		.17 / .05		.22 / .11	

Note. *$p \leq 0.05$

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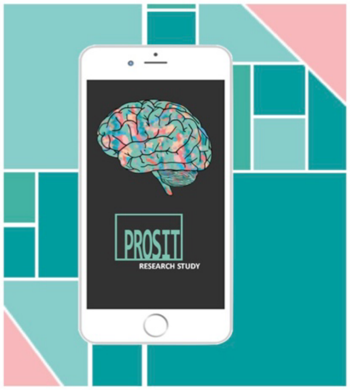
APPENDIX A RECRUITMENT POSTER



ARE YOU IN TREATMENT FOR A MENTAL DISORDER?

TAKE PART IN A RESEARCH STUDY!

WHO IS ELIGIBLE FOR THE STUDY?

1. Those between the ages of 10 and 21.
2. People diagnosed with a mental disorder, as well as healthy people or those without a diagnosis. Everyone is welcome.

WHAT IS THE PURPOSE OF THE STUDY?

We are interested in whether a smartphone app can use movements and social interactions to predict how well you are doing.

Can Twitter and Snapchat help us to improve treatment for mental disorders?

WHAT WILL YOU BE ASKED TO DO?

If you decide to take part, we would like you to:

1. Complete 3 surveys over the course of 6 months. Two 35-minute and one 15-minute online surveys.
2. Download our app for 3, two-week periods over 6 months.

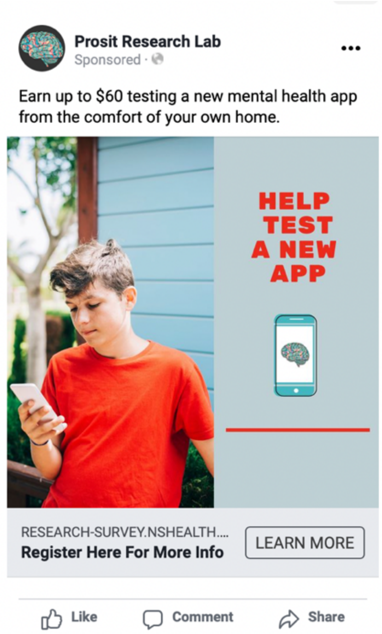
You will be reimbursed for your time, $20 for each survey completed, for a total of $60.

WHO ARE THE RESEARCHERS?

Dr. Sandra Meier (PhD; IWK, Dal)
Dr. Alexa Bagnell (MD; IWK, Dal) ; Dr. Lukas Propper (MD; IWK, Dal);
Dr. Patrick McGrath (PhD; IWK, Dal); Dr. Trish Pottie (PhD; IWK, Dal)

REGISTER USING THE LINK OR SCAN THE CODE:

APPENDIX B SOCIAL MEDIA ADVERTISMENTS



APPENDIX C RECRUITMENT BROCHURE

BENEFITS OF PARTICIPATION

Taking part in this study may help you find better ways of managing your mental health disorder.

This study will also help us to develop new treatments for teens with mental health disorders.

WILL I BE REIMBURSED FOR MY TIME?

Yes! You will receive $10 once you've completed each of the questionnaires and $40 for working with our app. So, if you complete the study, you will receive $70 by the end of the 6-month study.

ARE THERE DISADVANTAGES TO PARTICIPATING?

There are no drawbacks. All information is treated in confidence. Participation in the study is entirely voluntary and stopping the study has no influence whatsoever on the treatment offered by your health care professionals.

WHAT INFO WILL THE APP GATHER?

The app developed by the PROSIT group passively records how you socially interact for a two week period. We will register calls and messages, app usage, physical movement, and how close in proximity you are to other people via Bluetooth. For example, we will register how many calls and messages you make and receive, how many people you contact, when you contact them, and for how long you're speaking. We will also collect information on which apps you like to use, when and for how long.

Using the smartphone built-in sensors, GPS and accelerometer data, we will collect information to find out how much time you spend at home or outside, and how much you exercise. It's important to know that we will NOT review or record any of the content of your calls, messages, or tweets you make and receive. This means that your communications will be completely private; we will only see that you are communicating with your friends and family. We will also collect GPS data in a way that does not register exact locations to ensure your privacy.

WHAT HAPPENS WITH MY DATA?

All data is processed completely anonymously and will only be used for writing scientific articles and reports.

There will never any personal information revealed that could identify you.

TO REGISTER

To register to for the PROSIT study, please follow the link below:

APPENDIX D SCREEN FOR CHILD ANXIETY RELATED EMOTIONAL DISORDERS (SCARED)

Directions:
Below is a list of sentences that describe how people feel. Read each phrase and decide if it is "Not True or Hardly Ever True" or "Somewhat True or Sometimes True" or "Very True or Often True" for you. Then for each sentence, fill in one circle that corresponds to the response that seems to describe you for the last 3 months.

		0 Not True or Hardly Ever True	**1 Somewhat True or Sometimes True**	**2 Very True or Often True**
1.	When I feel frightened, it is hard for me to breathe	o	o	o
2.	I get headaches when I am at school	o	o	o
3.	I don't like to be with people I don't know well	o	o	o
4.	I get scared if I sleep away from home	o	o	o
5.	I worry about other people liking me	o	o	o
6.	When I get frightened, I feel like passing out	o	o	o
7.	I am nervous	o	o	o
8.	I follow my mother or father wherever they go	o	o	o
9.	People tell me that I look nervous	o	o	o
10.	I feel nervous with people I don't know well	o	o	o
11.	My I get stomachaches at school	o	o	o
12.	When I get frightened, I feel like I am going crazy	o	o	o
13.	I worry about sleeping alone	o	o	o
14.	I worry about being as good as other kids	o	o	o
15.	When I get frightened, I feel like things are not real	o	o	o
16.	I have nightmares about something bad happening to my par-ents	o	o	o
17.	I worry about going to school	o	o	o
18.	When I get frightened, my heart beats fast	o	o	o
19.	I get shaky	o	o	o
20.	I have nightmares about something bad happening to me	o	o	o

21.	I worry about things working out for me	o	o	o
22.	When I get frightened, I sweat a lot	o	o	o
23.	I am a worrier	o	o	o
24.	I get really frightened for no reason at all	o	o	o
25.	I am afraid to be alone in the house	o	o	o
26.	It is hard for me to talk with people I don't know well	o	o	o
27.	When I get frightened, I feel like I am choking	o	o	o
28.	People tell me that I worry too much	o	o	o
29.	I don't like to be away from my family	o	o	o
30.	I am afraid of having anxiety (or panic) attacks	o	o	o
31.	I worry that something bad might happen to my parents	o	o	o
32.	I feel shy with people I don't know well	o	o	o
33.	I worry about what is going to happen in the future	o	o	o
34.	When I get frightened, I feel like throwing up	o	o	o
35.	I worry about how well I do things	o	o	o
36.	I am scared to go to school	o	o	o
37.	I worry about things that have already happened	o	o	o
38.	When I get frightened, I feel dizzy	o	o	o
39.	I feel nervous when I am with other children or adults and I have to do something while they watch me (for example: read aloud, speak, play a game, play a sport)	o	o	o
40.	I feel nervous when I am going to parties, dances, or any place where there will be people that I don't know well	o	o	o
41.	I am shy	o	o	o

**For children ages 8 to 11, it is recommended that the clinician explain all questions, or have the child answer the questionnaire sitting with an adult in case they have any questions.*

Developed by Boris Birmaher, MD, Suneeta Khetarpal, MD, Marlane Cully, MEd, David Brent, MD, and Sandra McKenzie, PhD. Western Psychiatric Institute and Clinic, University of Pgh. (10/95). Email: birmaherb@msx.upmc.edu

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APPENIDX E CENTER FOR EPIDEMIOLOGIC STUDIES DEPRESSION SCALE (CESD)

DURING THE PAST WEEK	Not At All	A Little	Some	A Lot
1. I was bothered by things that usually don't bother me.	_____	_____	_____	_____
2. I did not feel like eating, I wasn't very hungry.	_____	_____	_____	_____
3. I wasn't able to feel happy, even when my family or friends tried to help me feel better.	_____	_____	_____	_____
4. I felt like I was just as good as other kids.	_____	_____	_____	_____
5. I felt like I couldn't pay attention to what I was doing.	_____	_____	_____	_____

DURING THE PAST WEEK	Not At All	A Little	Some	A Lot
6. I felt down and unhappy.	_____	_____	_____	_____
7. I felt like I was too tired to do things.	_____	_____	_____	_____
8. I felt like something good was going to happen.	_____	_____	_____	_____
9. I felt like things I did before didn't work out right.	_____	_____	_____	_____
10. I felt scared.	_____	_____	_____	_____

DURING THE PAST WEEK	Not At All	A Little	Some	A Lot
11. I didn't sleep as well as I usually sleep.	_____	_____	_____	_____
12. I was happy.	_____	_____	_____	_____
13. I was more quiet than usual.	_____	_____	_____	_____
14. I felt lonely, like I didn't have any friends.	_____	_____	_____	_____
15. I felt like kids I know were not friendly or that they didn't want to be with me.	_____	_____	_____	_____

DURING THE PAST WEEK	Not At All	A Little	Some	A Lot
16. I had a good time.	_____	_____	_____	_____
17. I felt like crying.	_____	_____	_____	_____
18. I felt sad.	_____	_____	_____	_____
19. I felt people didn't like me.	_____	_____	_____	_____
20. It was hard to get started doing things.	_____	_____	_____	_____

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APPENDIX F SELF-REPORT FORM MEASURE OF DSM-5 ADHD (ADHD-SR)

	Never or Rarely	Sometimes	Often	Very Often
1. Fail to give close attention to details or make careless mistakes in my work.	0	1	2	3
2. Fidget with hands or feet or squirm in my seat.	0	1	2	3
3. Difficulty sustaining my attention in tasks or fun activities.	0	1	2	3
4. Leave my seat in classroom or in other situations in which seating is expected.	0	1	2	3
5. Don't listen when spoken to directly.	0	1	2	3
6. Feel restless.	0	1	2	3
7. Don't follow through on instructions and fail to finish work.	0	1	2	3
8. Have difficulty engaging in leisure activities or doing fun things quietly.	0	1	2	3
9. Have difficulty organizing tasks and activities.	0	1	2	3
10. Feel "on the go" or "driven by a motor."	0	1	2	3
11. Avoid, dislike, or reluctant to engage in work that requires sustained mental effort.	0	1	2	3
12. Talk excessively.	0	1	2	3
13. Lose things necessary for tasks or activities.	0	1	2	3
14. Blurt out answers before questions have been completed.	0	1	2	3
15. Easily distracted.	0	1	2	3
16. Have difficulty awaiting turn.	0	1	2	3
17. Forgetful in daily activities.	0	1	2	3
18. Interrupt or intrude on others.	0	1	2	3

APPENDIX G PROSIT APPLICATION FUNCTIONS

The PROSIT application includes the following features (See Figure G1 below for visual overview of collected data). The application constantly collects inertial measurement unit data making use of the smartphone's built-in accelerometer, gyroscope, and magnetometer sensors. This enables the fine-grained estimation of physical activity, over and above what can be gleaned from Google Fit and Apple Health Kit data. Along with the inertial measurement unit data, the application has the ability to sample ambient light and noise via the smartphone's sensors further enhances the PROSIT applications measurement of sleep. The application permits the automatic collection of seven indices of phone use: SMS frequency, call frequency, notifications, screen-on time, installed apps, and app use time. The meta-data typed text is recorded, such as text length, number of letters, numbers, and emoticons used. The notification center is monitored to capture what music youth listen to across various music apps. Lastly, acoustic voice features are sampled through youth's audio diaries.

In addition to collecting aspects of youth's daily life behavior the PROSIT application records weather, battery life, and device information. The application also facilitates integration with wearable technology to collect raw data from wearable devices (e.g., wrist wearables that measure actigraphy and heart rate). This integration of wearable technology improves efficiency of data collection. Finally, the application can send questionnaires to user's smartphone. The questionnaire responses can be accessed remotely. New questionnaire files can be easily created either manually or authored as REDCap data dictionaries.

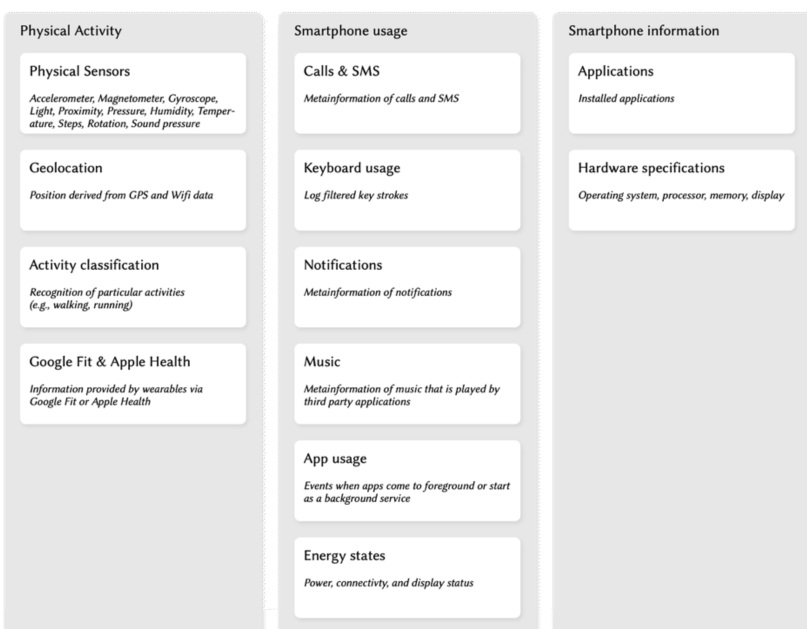


Figure G: Overview of collected data. The PROSIT Android and iOS applications collect data that reflect the physical activity, sleep, and the smartphone usage of the user, as well as more stable smartphone specifications.

APPENDIX H PROSIT APPLICATION PRIVACY

One of the main considerations guiding the design of the PROSIT application was privacy and encryption. To detect risk states before they become mental health crises the PROSIT application collects a massive amount of personal data, so it is imperative that these data remain secure and cannot be used to identify youth. To ensure data privacy, we have implemented a detailed security protocol to deidentify and encrypt all mobile-sensed data. First the identity of youth is anonymized. Neither the name, the phone number, nor the phone ID is stored. Instead, the PROSIT tool assigns youth a nine character long unique identifier, called "Study ID", to each user. Also, all sensitive information collected by the PROSIT tool is stored inside a private database, which is not accessible by any third-party software. Obviously, these basic first steps do not safeguard the actual content of the data.

Thus, state-of-the-art encryption is implemented in the data security pipeline. After the sensors generate data, the data are immediately encrypted by the PROSIT application using 128-bit Advanced Encryption Standard encryption, a government standard endorsed by the US National Institute of Standards and Technology. Upon encryption, the unencrypted data are immediately deleted. Moreover, all phone numbers and names of persons are irrevocably anonymized by a cryptographic hash function. The big benefit of cryptographic hashing is that it is still possible to inspect social networks of youth, since the same contact on youth's phones will result in the same hash value. Also, there is an additional security protocol in place to handle all typed text, all typed text can be fully read by the PROSIT application. The content of all typed text will not leave the phone but will be analyzed directly on the device. Specifically, the tool computes the text length, number of letters, numbers, and emoticons used. During data transfer from mobile phone to server, the data is encrypted using RSA/ECB/OAEPWithSHA-1AndMGF1Padding encryption algorithm. Every hour, all mobile-sensed data is transferred to the database on a secure server through the RESTful application programming interface if the PROSIT application is on the Internet, otherwise the data is locally stored until the device gets an Internet connection. After the successful data upload to the secure server at our clinic, the PROSIT tool deletes all mobile-sensed data from the phone's memory.

The PROSIT backend software is installed on the secure server at our clinic ensures that the data is only send to this secure server, protected by Firewall. The PROSIT backend consists of a set of Docker services. They manage the authentication of users of the PROSIT application, process data upload, and provide a dashboard to manage users and to access data. A reverse proxy Nginx server forwards the incoming requests, ensures secure HTTPS connection, and mitigates Distributed Denial-of-Service attacks. A web server then processes incoming requests. We developed the webserver with the Meteor web framework. The web server provides a REST API for mobile clients. The API provides endpoints to request authentication and to upload data. We follow the JSON Web Token standard to authenticate mobile clients and permit data upload. The web server furthermore provides a dashboard. The dashboard is a browser-based user interface for the administration of users and the access of collected data, also the dashboard is password protected. A MongoDB database stores all textual data and a docker volume stores uploaded image and audio files. The backend has its own access permission system ensuring no third parties have access to the stored data. Both, the PROSIT application and backend are designed to use SSL for data transmission. SSL encrypts data when it is sent over the Internet, and it is the de facto standard for high level of data security. See Figure H1 below for the architecture of the PROSIT backend.

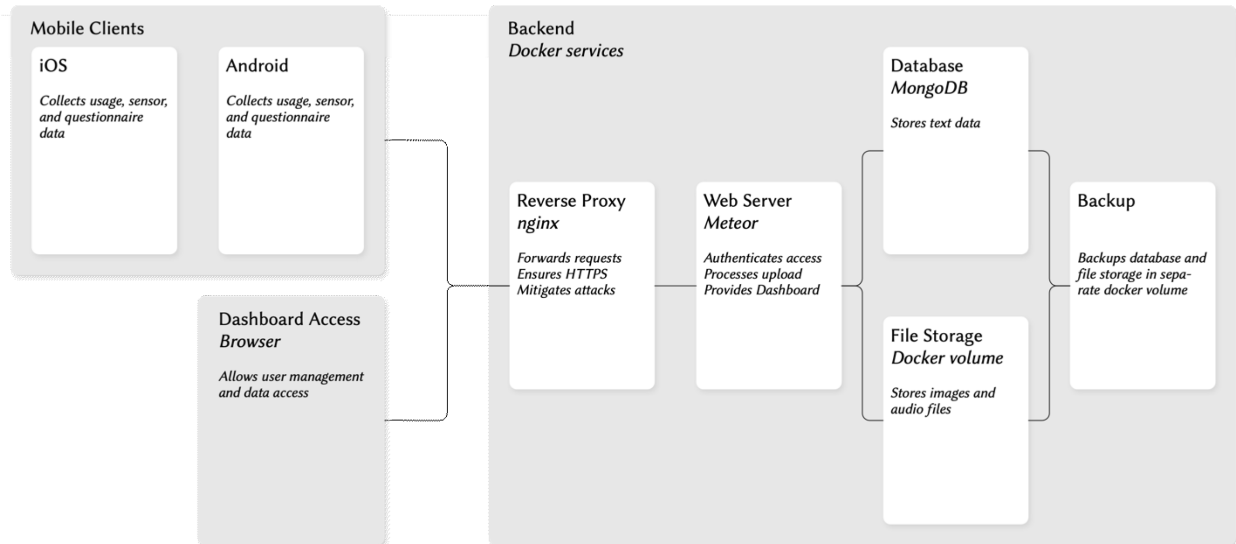


Figure H1: The architecture of the PROSIT backend. The backend consists of Docker services that manage user authentication, upload of collected data, and access to the dashboard.

APPENDIX I PROSIT APPLICATION INSTRUCTIONS

PROSIT for iOS

Hello, my name is Lucy.

I will explain how you can install PROSIT on iPhone and what you have to do during the study.

Please follow the next steps to install PROSIT on iPhone. Depending on your phone version, some steps might look a bit different from our screenshots: In this case, follow the instructions on your phone to give permissions.

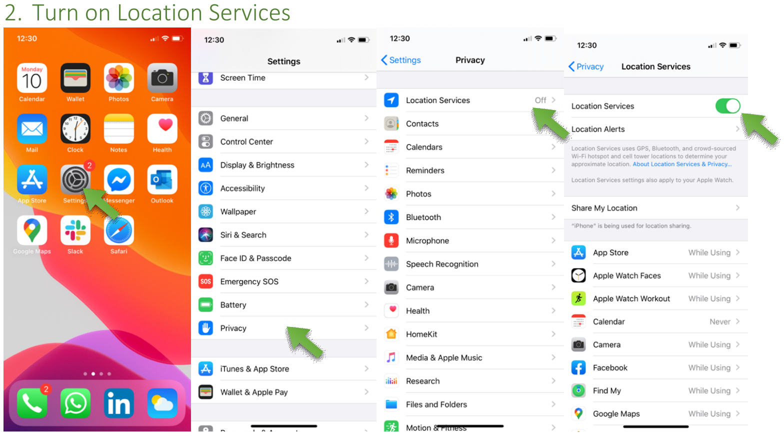
If you have any questions or run into any issues, don't hesitate to send me an email: *PROSIT@iwk.nshealth.ca*

Installation steps

1. Connect to Wi-Fi

Go to Settings -> WiFi -> Turn on

2. Turn on Location Services

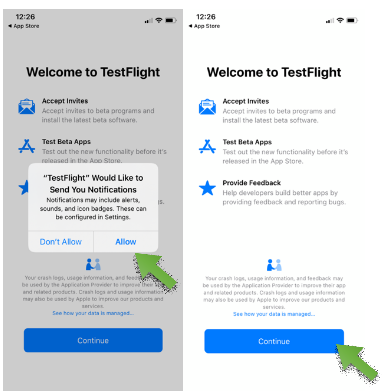


3. Install TestFlight

Go to the App Store and search for "TestFlight." Then tap the download symbol to install this app. TestFlight is provided by Apple and allows you to install apps in testing stages on your phone.

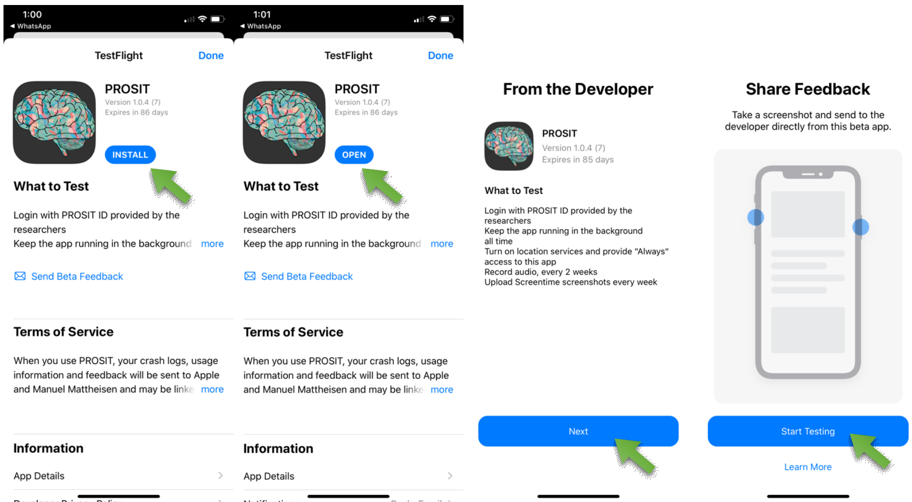
4. Agree to TestFlight Terms and Conditions

Open the TestFlight app, allow notifications and agree to terms and conditions.



5. PROSIT Installation

1. Follow this link to download the app: *https://testflight.apple*[redacted]
2. Click “INSTALL” for the PROSIT App.
3. Once installation is complete, click “OPEN”
4. You will be taken through screens that give you a summary of how to use PROSIT. Click “Next”
5. The final screen will instruct you on how to take a Screenshot in case you need any technical support from us. Click “Start Testing”

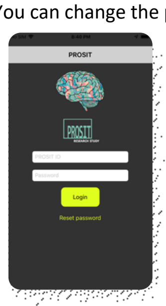


Congratulations! now you have successfully installed our app, lets proceed with initial setup.

PROSIT Login and Setup

1. Login

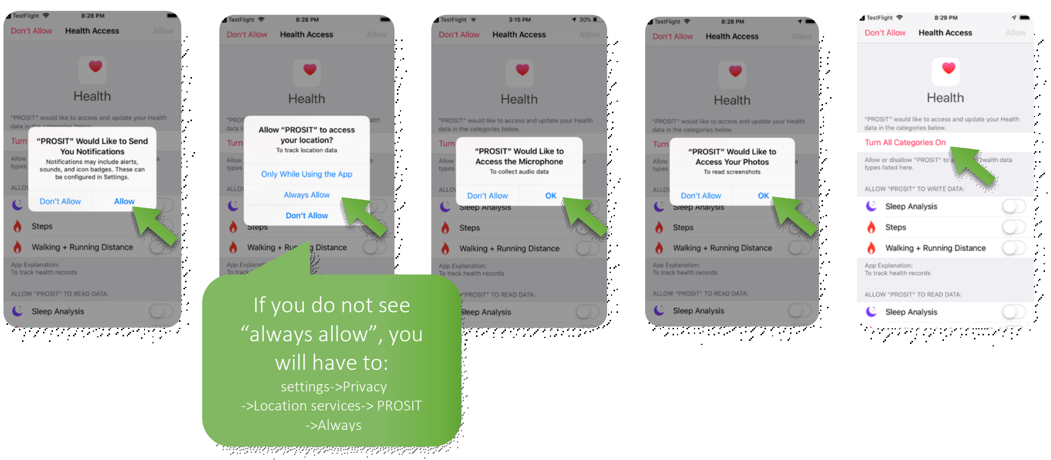
Open PROSIT and enter the User ID and the Password that we provided to you by email.
You can change the password if you would like, using the “Reset password” link at the bottom of Login page



2. Allow permissions

Give all permissions requested by the app:

- **Send you notifications**: To remind you to record speech samples and upload screenshots.
- **Location**: Location will only be recorded in accuracy of 20 m radius; details of the street names are collected but not the exact building number.
  - If you have iOS 12: Please select "always allow,"
  - If you have iOS 13: Go to Settings → Privacy → Location Services → PROSIT → Always
- **Access to photos:** You will have control over selecting pictures to upload, we can only see the Screentime screenshots you upload.
- **Access to microphone:** We will only access audio that you record in the 90 second voice sample. Noise during sleep is detected as ambient noise, meaning that is it not recorded only detected to determine if there is background noise in the environment.
- **Access to Health app:** We will get information about your sleep, steps, running or walking distance. Click "Turn All Categories ON" and then click "Allow."



Installation finished

🥳

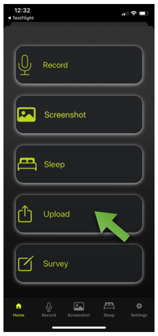
Super, you finished the installation. If something didn't work, send me a mail: *PROSIT@iwk.nshealth.ca*
I will help you.

Most of the time, the app is running the background, and you need to do nothing. However, we sometimes need your help to record Audio samples and take a screenshot of Screen Time. In the following, I will explain how you can do this.

Now I will show you what to do during the next two weeks:

1. Overview

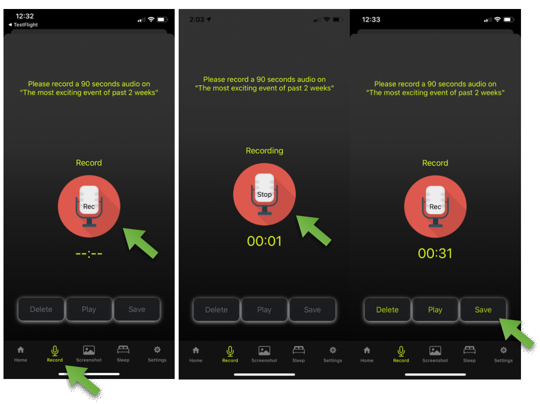
- You can see buttons for Record, Screenshot, Sleep, Upload and Survey on the home screen.
- Also, you will see the first three of these options in the bottom tab bar too. You can use either option to access the features
- Right now, click on the "Upload" button, so the researchers can confirm your app is properly activated.



2. Audio

Once every two weeks, you will receive notification to talk for 90 seconds about "The most exciting event of the past two weeks."

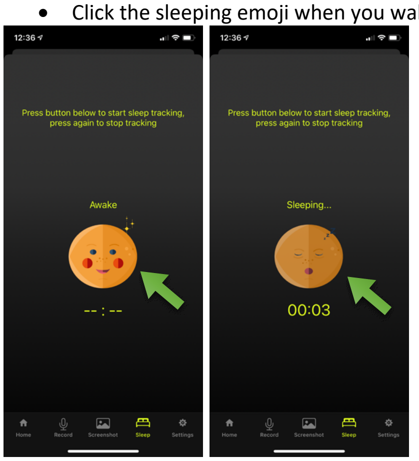
- Go to the "Record" screen and hit the "Rec" button to start talking.
- When done talking, stop recording by clicking the same red record icon which now shows "Stop."
- You can listen to your recording by pushing the "Play" button in the middle.
- Delete a recording by pressing "Delete" option.
- When you are finished recording push "Save" button. Note. Your recording will not be saved unless you press the Save button



3. Sleep

Every evening when you go to bed the app will ask you to record you sleep.

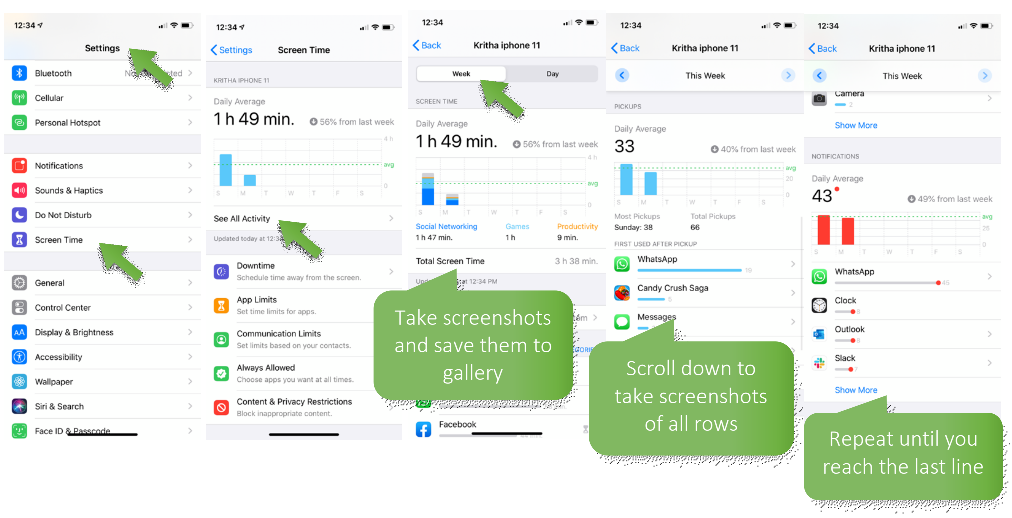
- Please go to the "Sleep " screen and click on the emoji the timer below the emoji will start ticking.
- Click the sleeping emoji when you wake up the morning.



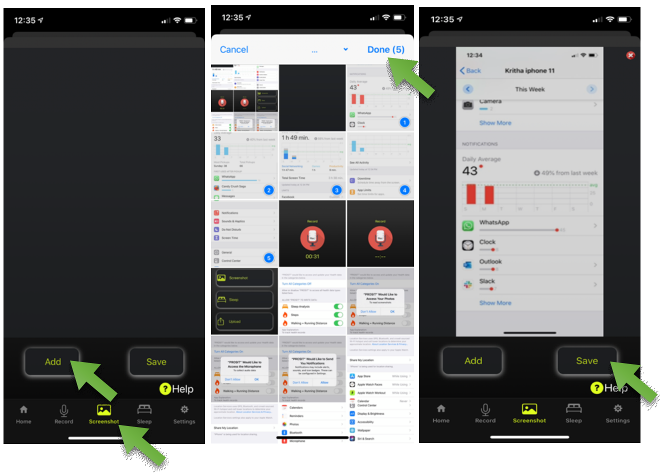
4. Screen Time

We have a video explaining how to properly capture your screen time. You can watch it by using the Help icon Help at the bottom of Screenshot page on the PROSIT app. Please upload your screen time right now, we will also ask you to do it again in a few days.

- Open Settings and select "Screen Time."
- Select "See All Activity." Select "Week."
- Take a screenshot by pressing the Home button and the button on the right side of the phone.
- Continue taking screenshots to until you reach the end of the page. This will take 3-4 screenshots.

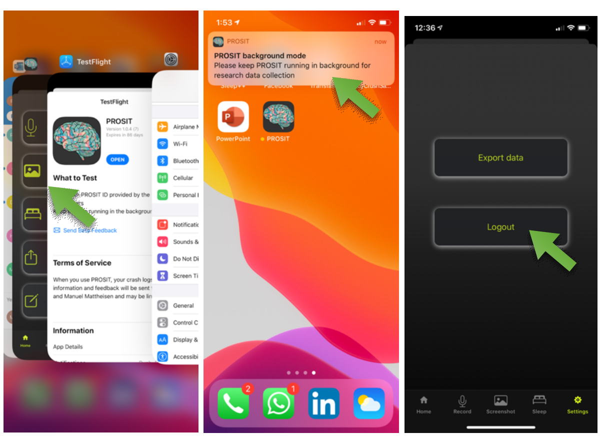


- Now open the PROSIT app, go to the Screenshot page and click “Add” button.
- Select the Screen Time screenshots you wish to upload and click “Done.”
- You can always review the screenshots by swiping left or right on the screen.
- You can delete unwanted pictures by clicking the small button on top of each image.
- Click “Save” after selecting and verifying screenshots.

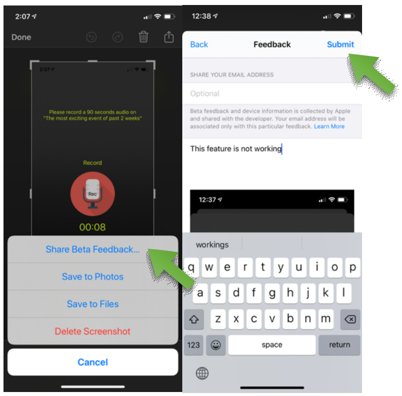


Reminders!

- Make sure PROSIT is always running in the background.
- If you accidentally close the app, you will receive a notification to open it.
- If prompted by the researchers, you can logout using “Logout” option in Settings page of PROSIT app.



- If you face any technical issues, take a screenshot.
- Choose “Share Beta Feedback…” option
- Type any description you wish to provide.
- Click Submit.



That’s it! Thank you!

🤗🙏

- The app will automatically upload data to our secure servers frequently, whenever you are connected to WiFi, so don't worry; we will not utilize your mobile data.
- If you have any questions or run into any issues, don’t hesitate to email me: *PROSIT@iwk.nshealth.ca*
- You can also watch a video that explains the app on this link: [redacted]

Thank you so much for being part of our study and helping us with our research!

APPENDIX J COPYRIGHT INFORMATION

Parts of this manuscript have been published n JMIR mHealth and uHealth

(https://mhealth.jmir.org/2021/10/e20638)

MacLeod L, Suruliraj B, Gall D, Bessenyei K, Hamm S, Romkey I, Bagnell A, Mattheisen M, Muthukumaraswamy V, Orji R, Meier S. A Mobile Sensing App to Monitor Youth Mental Health: Observational Pilot Study. JMIR Mhealth Uhealth 2021;9(10):e20638
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