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The use of digital phenotyping to investigate the relationship between digital media use and mental health in a cohort of clinical adolescents

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THE USE OF DIGITAL PHENOTYPING TO INVESTIGATE THE RELATIONSHIP BETWEEN DIGITAL MEDIA USE AND MENTAL HEALTH IN A COHORT OF CLINICAL ADOLESCENTS

by

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DEDICATION

Dedicated to the memory of my step-father
Gary Albert Schad

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ABSTRACT

Background: As smartphone devices have become a ubiquitous part of our modern lives, parents and clinicians have become increasingly concerned about the effects of digital media use on the mental well-being of adolescents and young adults. Smartphone ownership in youth has increased significantly over the last decade, paralleling the rise in mental health disorders. This study seeks to use the digital phenotyping (DP) methodology to elucidate these relationships. Most studies examining these variables use cross-sectional data in healthy adolescents. To our knowledge, no studies have used DP methodology to characterize the relationship between digital media use, depression and anxiety in a population of clinical adolescents.

Methods: 50 adolescent and young adults between the ages of 12-23 receiving outpatient mental health services from a community hospital network in the greater Boston area were enrolled. Participants installed an application on their personal smartphones that collected daily surveys that captured mood symptoms, digital media use (screen time, social media time, and top apps used [active data]), and that also continuously captured sensor data (GPS and accelerometer [passive data]) over six weeks.

Results: Using linear regression and multilevel modeling, no significant associations were found between screen time or social media time, and anxiety and depression symptoms. Productivity apps were used significantly more in those with no depression symptoms than in those with moderate to severe levels of depression.

Conclusion: Our study results challenge the present intuition that the amount of digital media use negatively impacts mental well-being in youth. Total screen time and social media time measures may be insufficient when attempting to assess the impact of digital media engagement on youth. Additionally, the results of our study suggest that the types of apps used by youth may depend on an individual's mood severity. Although not without limitations, DP studies may be the ideal methodology for capturing with greater granularity digital use behavior and its association with mood symptoms in adolescents.

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LIST OF ABBREVIATIONS

AAP .... American Academy of Pediatrics

ALS .... Amyotrophic Lateral Sclerosis

ASD .... Autism Spectrum Disorder

CDC .... Centers for Disease Control and Prevention

CHA .... Cambridge Health Alliance

DP .... Digital Phenotyping

DSM .... Diagnostic and Statistical Manual of Mental Disorders

ECG .... Electrocardiography

EHR .... Electronic Health Records

EMA .... Ecological Momentary Assessment

GAD-7 .... General Anxiety Disorder-7

GPS .... Global Positioning System

ICD .... International Statistical Classification of Diseases

LAMP .... Learning, Assess, Manage, Prevent

PDA .... Personal Device Assistant

PHQ-9 .... Patient Health Questionnaire-9

SES .... Socioeconomic Status

INTRODUCTION

Evidence suggests that increased digital media use through smartphones may contribute to mental health disorders such as anxiety and depression. Most existing studies explore this relationship in adults. Our research is interested in investigating this relationship in clinical adolescents, e.g., youth with mental health disorders because this is a traditionally under-studied population. Recent evidence suggests youth with mental health issues are far more vulnerable to engaging in problematic digital media use. Additionally, most adult psychiatric illnesses originate in childhood; thus, there is a growing momentum to study, identify and treat mental disorders as early as possible. However, adolescents tend to be unreliable self-reporters of their symptoms. Clinicians are challenged to find ways to capture objective symptom and behavior information to improve diagnosis and treatment. Digital Phenotyping (DP) may bridge this gap by capturing active (self-report surveys) and passive data (objective data collected through sensors in real-time on the smartphone) sampled repeatedly over time. This study aims to evaluate possible relationships between active and passive data and consider the impact of digital media use on mental health in clinical adolescents through DP methodology.

Smartphones and Mental Health

Since the advent of smartphone technologies about a decade ago, ownership and use of smartphones worldwide have grown rapidly. According to recent Pew Research Center data, more than 2.5 billion people worldwide own smartphone devices. More young people under the age of 35 own and use smartphones for social media and the internet than any other age group (L. Silver, 2019). With this surge in smartphone use and ownership, there are growing concerns and increasing interest in how digital media consumption impacts adolescent well-being. In 2012, the American Academy of Pediatrics (AAP) elevated the issue of digital media use in children and adolescents to a top priority for research (Shifrin et al., 2015). Organizations such as the AAP have published recommendations for limiting screen time on digital devices because of concerns of risk to physical and mental health, such as adverse effects on sleep and exercise, and exposure to inappropriate content or cyberbullying (*Media and Children Communication Toolkit*, 2016; Media, 2016)

Smartphone ownership in children is increasing, as seen in the Common Sense Census report in 2019 (Rideout & Robb, 2019c). Over half of kids age 11 have their own smartphone, and by 12, nearly two-thirds do. Overall ownership between tweens and teens has increased by almost 20% from 2015 to 2019. (**Figure 1 & Figure 2;** Rideout and Robb, 2019). Simultaneously, there has been a significant increase in the prevalence of depression in youth, especially in adolescents aged 12-20, paralleling the rise of smartphone ownership **(Figure 3;** (Mojtabai et al., 2016; Twenge et al., 2019).

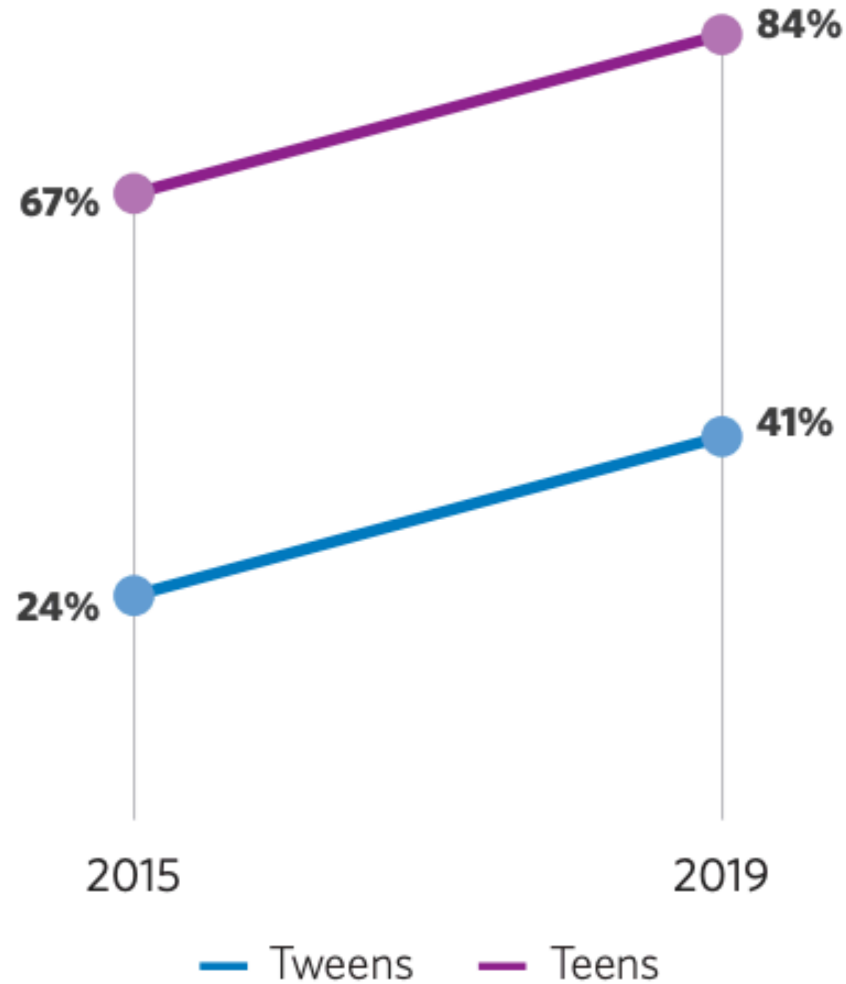

Figure 1. Ownership of smartphones in Tweens and Teens in 2015 and 2019.
(Rideout & Robb, 2019a)
The figure shows the general increase across the two age categories over time. Tweens are defined as 8 to 12 year-olds, and Teens are defined as 13 to 18 year-olds.

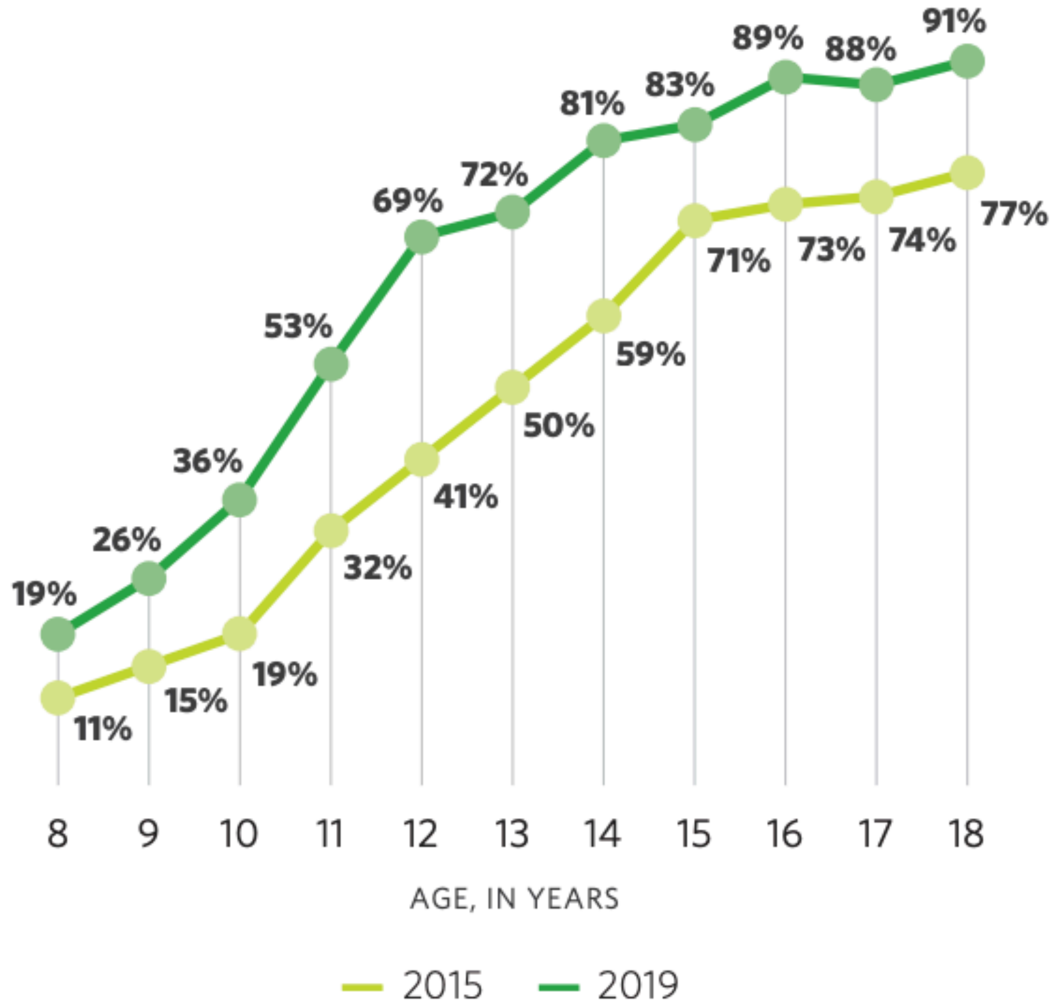

Figure 2. Smartphone ownership in 2015 vs. 2019. (Rideout & Robb, 2019a)
Increase of smartphone ownership by age over time. The most significant increase can be seen in the tweens, particularly in 12 year-olds.

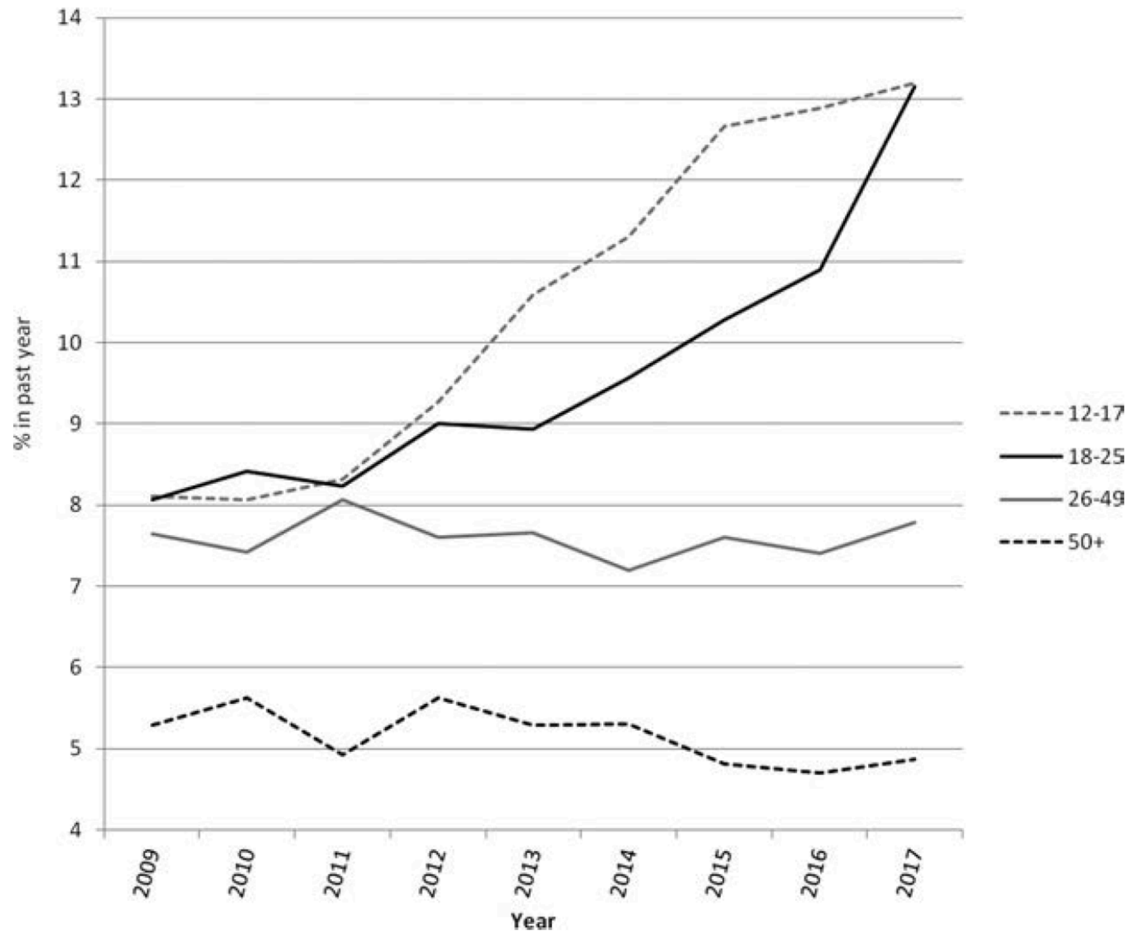

Figure 3. The occurrence of a major depressive episode in the last 12 months by age. (Twenge et al., 2019)
Drawn from the National Survey on Drug Use and Health, N = 611,880

A growing body of research suggests that there may be a connection between increased smartphone screen time and social media use and mental disorders such as depression and anxiety in youth (Abi-Jaoude et al., 2020; Karim et al., 2020; Twenge et al., 2017). Increased recreational screen time, especially on tablets and mobile phones, has been negatively associated with physical self-concept (Babic et al., 2017). Digital platforms such as social media encourage adolescents to share pictures of themselves, leading to unhealthy comparison and pressure to conform to idealized physical attributes, contributing to a decreased sense of well-being (Kross et al., 2013; Eyal and Te'eni-Harari 2013). While some young adults feel mobile phones facilitate connectiveness by promoting personal relationships and access to social support groups, usage of mobile phones may not confer the same advantages as face-to-face interactions (Thomée et al., 2010). Teens and young adults with existing moderate to severe depressive symptoms report more negative experiences through social media compared to non-depressed youth (Rideout, 2018). In fact, studies have found that greater levels of reported mobile phone use were associated with significantly higher depression scores for adolescents at their one-year follow-up assessment (Bickham et al., 2015). Despite these studies, the impact of screen time and digital media use on mental health in youth remains greatly contested due to methodological limitations in the existing studies. For example, a majority of studies heavily rely on cross-sectional data which makes it impossible to determine if increased digital media causes mental health disorders or if individuals with mental health disorders are simply more likely to engage in more digital media use. Additionally, the use of "total screen time" as a primary measure for assessing digital media use risk is increasingly controversial as more adolescents are using digital devices constructively for school work and communication with family and friends (C. L. Odgers & Jensen, 2020).

Why It's Important to Focus on Mental Health in Youth

While there is a push towards early diagnosis and treatment of mental disorders, there is also a strong impetus to understand mental disorders' triggers, particularly in youth (Kieling et al., 2011; Merikangas et al., 2010). Studies have shown that 75% of adults with psychiatric disorders received their diagnoses before age 18. Researchers have argued that most adult disorders should be considered extensions of juvenile disorders (Kim-Cohen et al., 2003) and that nearly half of the lifetime cases occur in childhood (Kessler et al., 2005). Given the long-lasting impact of mental illness throughout adulthood, Kieling et al. called for it to be considered a global health agenda and underscored the importance of addressing mental health disorders early in development (Kieling et al., 2011). Additionally, nearly a quarter of youth in the United States met the diagnostic criteria for a mental health disorder with severe impairment across their lifetime, suggesting early treatment and prevention in youth should be the primary focus (Merikangas et al., 2010). Considering the rate at which adolescent mental health disorders transition into adulthood, and the potential risk for a lifetime of impairment, the ability to identify and treat symptoms early is invaluable.

Retrospective Self Report vs. Ecological Momentary Assessment

Clinicians and researchers often use retrospective self-reports as a primary metric for assessing mental well-being and making diagnostic and treatment decisions. Up to this point, these surveys have typically been paper-based and are widely used to gain insight into how patients think and feel. Administered during clinic visits, these survey instruments usually require respondents to evaluate past experiences that have occurred in the last few days, weeks, or months. While these psychological assessment tools are well-validated, there has been increased concern regarding the accuracy and reliability of these tools as they could be vulnerable to cognitive biases. For example, intense experiences or negative states like anxiety or depression are often reported with higher ratings when recall of an event is greater than a week compared to surveys conducted daily (Clark & Teasdale, 1982; Schuler et al., 2021). This phenomenon could be attributed to memory bias as people tend to have better memories of intense emotional events over less intense events, resulting in over or under-reporting symptoms (Schwarz, 2012). Complications also arise if too much time has elapsed between an event of interest and the time of recall. In these cases, respondents will backfill their answers by aggregating their experience, further obscuring the ability to capture symptom and behavior change over time accurately, which can occur in both clinically depressed individuals or controls (Ben-Zeev et al., 2009; Schwarz, 2012). Many researchers propose that real-time data capture can eliminate memory-related bias through Ecological Momentary Assessment methods (aan het Rot et al., 2012; Oreel et al., 2020; Schwarz, 2012).

Ecological Momentary Assessment or EMA collects data by repeated sampling of subjects to capture representative momentary experiences (Stone & Shiffman, 1994). For example, subjects are provided with a device like an electronic diary to submit their daily responses (Shiffman et al., 2008). The cognitive biases resulting from delayed recall in retrospective self-reports are greatly diminished by asking subjects to report their experiences and symptoms daily. Other benefits are also seen when researchers switched to EMA methodology. A recent review on studies of mood disorders in children and adolescents using EMA found that the adherence to study protocol was high as well as improved patient insight and awareness of psychiatric symptoms (Baltasar-Tello et al., 2018). Traditionally, longitudinal studies tend to suffer from low response rates; therefore, the benefits of increased protocol adherence in EMA studies make it an ideal tool for researchers (Gustavson et al., 2012; Freedman, Thornton, and Camburn, 1980). While EMA used to be limited by methodology requiring subjects to carry specialized computer devices such as an electronic diary or personal device assistant (PDA), the ease with which EMA can be adopted for personal digital devices, such as the smartphone, has increased the feasibility and utility of EMA in clinical research (Ram et al., 2017; Runyan et al., 2013).

EMA minimizes both cognitive bias and maximizes ecological validity, but still shares some of the same weaknesses of retrospective self-reports. Because EMA relies on participant input, it is still susceptible to other biases such as social desirability bias (Robbins & Kubiak, 2014). Social desirability bias occurs when subjects chose responses that are perceived to be socially desirable. This is problematic, especially with stigmatized health conditions such as depression, since it can result in underreporting of symptoms (Latkin et al., 2017). The frequency of administered surveys in EMA may also be cumbersome and pose a potential barrier for long-term follow-up (Torous et al., 2016).

For EMA methods to become a suitable tool for studying lifelong illnesses, such as many psychiatric disorders, continual measurements must be conducted sustainably and unobtrusively. The solution may be found in a new methodology called Digital Phenotyping, or DP.

Digital Phenotyping

Digital Phenotyping is formally defined as "moment-by-moment quantification of the individual-level human phenotype in-situ using data from personal digital devices," specifically smartphone devices (Onnela & Rauch, 2016; Torous et al., 2015). Because smartphone devices are now ubiquitous and often possess various sensors (e.g. GPS, accelerometer), DP technology offers a unique opportunity to obtain continuous high-fidelity data on human behavior. Digital Phenotyping methodology can be applied through the development of a smartphone application designed to collect two subtypes of data, active and passive (Torous et al., 2015).

Active Data

Active data is any data acquired from direct participant input and can take the form of self-report tasks or cognitive assessments. For example, studies focused on mood disorders may frequently administer psychiatric symptom scales that allow clinicians to monitor mood symptoms over time (e.g., the PHQ-9 and GAD-7 to measure depression or anxiety symptoms, respectively) (Kroenke et al., 2001; Spitzer et al., 2006, p. 7). Surveys that ask participants to report their daily activities, like total hours spent on their phone or social media, physical activity like total daily step count, or even medication adherence, also count as active data. In a recent ALS study, finger tapping and speech recordings were another form of collectible active data (Berry et al., 2019). Cognitive assessments, which are considered active data, may take the form of short games that measure working memory or impulsivity (Tong et al., 2016).

Passive Data

Passive data is any data that is not the result of participant-generated responses and is captured through sensors on the smartphone. Physiologic and behavioral information is often captured as passive data. Examples of sensors commonly used to infer mobility include GPS, accelerometers, and Bluetooth. In Barnett et al's study, GPS measurements were used to extract information about distance traveled between significant locations, circadian rhythm, positional entropy, and amount of time spent at home (Barnett & Onnela, 2018). Wearable devices that use accelerometers can be used to evaluate physical activity and sleep efficacy, while sensors that monitor skin conductance and skin temperature can help measure the sympathetic nervous system's stress response and functioning (Wen et al., 2018; Smets et al. 2018). Information captured by sensors and software regarding phone screen on-off state, when combined with accelerometer data, could help develop an algorithm to infer sleep behavior, providing insight into a subject's circadian rhythm. Such information can be collected without interfering with an individual’s natural behavior, overcoming a major challenge in sleep studies (Abdullah et al., 2014).

Benefits of DP Generally

By leveraging a widely adopted technology ecosystem, DP methodology confers the advantage of being highly scalable and cost-effective. From a research perspective, DP could lessen the logistical burden of studies, a common barrier to recruitment and retention in clinical research (S. Ross et al., 1999). Increasing the ability to enroll research subjects would improve its power and expand its overall generalizability to the study population of interest. Furthermore, because DP enables the collection of both objective and subjective measurements, researchers can better corroborate reported symptoms against clinically validated outcome measures, improving a researcher’s insight into a patient’s functioning.

In the clinical setting, patients with mental health or substance use disorders face barriers in getting the regular and timely follow-up care they need. A few such examples of said barriers include lack of transportation or the time burden of traveling to and waiting for their in-clinic appointments (L. E. Ross et al., 2015). Especially for those from socioeconomic status (SES) disadvantaged backgrounds, the resources to physically attend clinics and appointments are common gatekeepers to care. These issues with access could be readily addressed by deploying DP as a cost-effective method for remote symptom and behavior monitoring (D. Silver et al., 2012; Syed et al., 2013).

The recent COVID-19 pandemic has further impacted access to healthcare for many patients. In a study published by CDC, nearly 40% of U.S. adults delayed or avoided receiving medical care for chronic and acute health conditions since the pandemic's onset because of safety concerns (Czeisler, 2020). This underscores the importance of developing methods that allow patients to access and communicate with their healthcare team easily from a remote setting (Monaghesh & Hajizadeh, 2020). As more studies identify clinically actionable targets using DP, it holds the potential to bridge gaps in care through early digital interventions.

Potential of DP for Clinical Application

Because mental health disorders cannot yet be diagnosed with biological tests, the early identification of markers that might better aid diagnosis and relapse in psychiatric illness is of utmost importance. Collection of passive data from smartphones (GPS and accelerometer sensor data) corroborated with self-reports of mental health symptoms may reveal clinically relevant markers for early diagnosis, improve condition monitoring, and possibly even aid in relapse prevention (Huckvale et al., 2019).

The existing care model for people with mental health disorders - such as those with schizophrenia- relies on waiting for a major psychiatric episode to occur, which often leads to hospitalization before intervention and treatment are provided. Studies looking at service utilization over ten years in patients with schizophrenia revealed that relapse was the leading cause for readmissions; early identification and intervention were important in decreasing readmission rates (Chi et al., 2016). Readmissions are problematic as they are costly and are likely due to inadequate monitoring through community-based aftercare and medication adherence (Heslin & Weiss, 2006; Vigod et al., 2013).

Barnett et al. explored the feasibility of using DP to predict relapse in patients with schizophrenia. This study followed patients who were undergoing active treatment for three months. Patients installed a research app that collected daily surveys (active data) and sensor information (passive data). The app captured social behavior and mobility patterns over time and detected "anomalies" in behavior two weeks before the patient experienced a relapse (Barnett et al., 2018). Powered with the predictive information from DP, clinicians would be able to intervene before a patient's symptoms escalate to dangerous levels, which would dramatically improve patient outcomes and reduce unnecessary medical spending.

With digital technologies like wearables and smartphones becoming a common part of our lifestyles, there has been an interest in identifying digital biomarkers that could offer actionable insights into our health (Wang et al., 2016). Until recently, most studies looking to capture digital biomarkers have suffered from small sample sizes, making the studies underpowered with resultant data difficult to analyze (Huckvale et al., 2019). Smartphone applications built to collect information for Digital Phenotyping can be programmed to work across multiple operating systems (iOS or Android), allowing easy deployment on most devices. The ease and accessibility of DP methodology could help researchers design studies that reach more people more expeditiously and improve the identification of biomarkers through more robust data analyses (Torous et al., 2016).

Current DP Research

The call for less resource-intensive methods for monitoring patients with psychiatric illnesses has led to a growth in studies examining the validity and use of DP. However, this methodology is in its infancy, and best practices are still being developed. The majority of existing studies using DP focus on adult populations, with autism spectrum disorder (ASD) and depression being the most commonly studied mental health topics. (**Figure 4;** Liang, Zheng, and Zeng 2019).

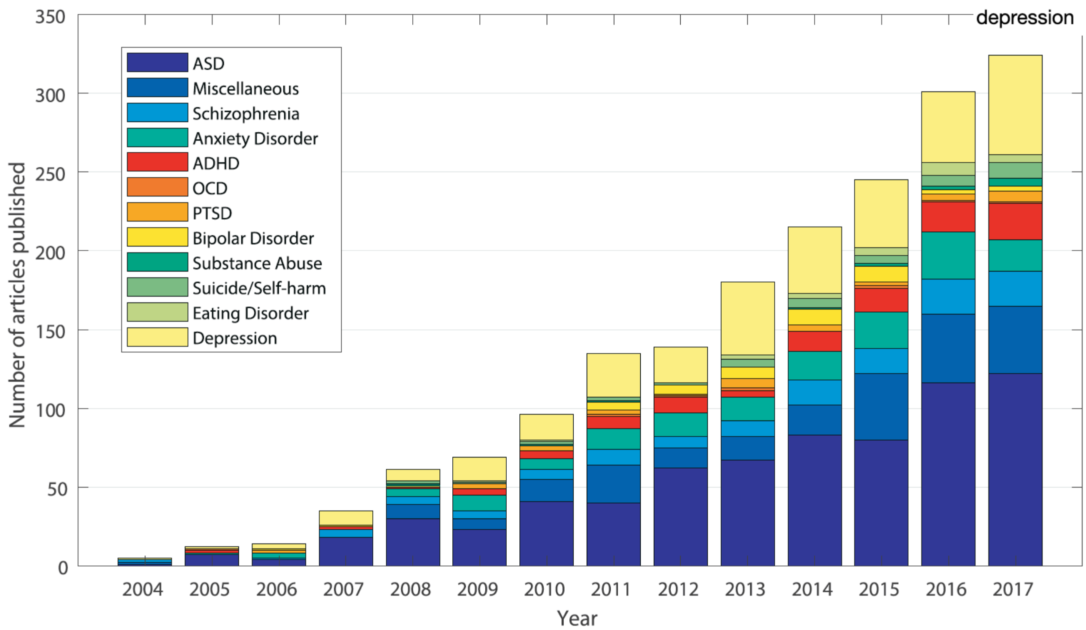

Figure 4. Increase in studies for mental health using Digital Phenotyping. (Liang et al., 2019)

A majority of DP studies focus on ASD and Depression.

DP and ASD

Individuals with autism spectrum disorder struggle with communication and may not be able to provide reliable self-report on their symptoms (American Psychiatric Association 2013). Existing diagnostic tools for ASD tend to over-diagnose, while observational methods tend to miss this disorder's signs and symptoms (Bishop and Norbury 2002; Filipek et al. 2000). The ability to accurately diagnose ASD benefits from a multidisciplinary approach that requires significant resources making it time-intensive (De Los Reyes et al., 2015). Ness et al. sought to improve instruments that can detect and capture changes in ASD symptoms over time using DP. Their observational study used wearable sensors to monitor physical activity and electrodermal activity continuously, allowing researchers to detect repetitive movement episodes, sleep pattern changes, and sympathetic arousal. Caregivers answered daily logs regarding ASD participant mood and behavior and tracked events of interest on either a smartphone or web-based application. Caregiver reports and biosensor data were then compared to psychometrically standardized tests and found to be highly correlative. Additionally, the sensors were able to detect features that distinguished ASD participants from typically developing participants. Although the study encountered some technical difficulties with electrodermal sensors, overall, the study showed strong potential for using DP methodology in future interventional studies in ASD (Ness et al., 2019).

DP and Depression

Depression is the second most frequently studied topic utilizing DP methodology, after ASD (Liang et al., 2019). Depression is significantly associated with morbidity and mortality, and undiagnosed depression can lead to long-term disability (Fawcett, 1993). A well-known characteristic of depression is psychomotor impairment, decreased motivation, and physical activity (Buyukdura et al., 2011). Therefore, researchers interested in the relationship between mood symptoms and an individual's movement may find DP to be a suitable methodology for their studies because of its ability to infer mobility through GPS sensors.

Saeb et al. explored the correlations between depression severity and behavior patterns using DP. Adults were recruited from the community and asked to install a smartphone app that could record GPS locations and phone usage. Depression severity was measured with the PHQ-9 survey and compared to the GPS and phone usage logs. The study found a significant negative correlation between rated depression severity, entropy, and circadian movement. People tended to visit fewer locations and had less regular movement when they felt depressed, supporting prior findings that mood symptoms and physical movement are interconnected (Saeb et al., 2015).

Another study examined the effects of depression on mobility and travel radius in women with perinatal depression. The subjects were followed over eight weeks and were asked to download a mobile app designed for android phones. The app passively collected velocimeter sensor data where distance traveled on foot and radius of travel could be calculated. Validated scales for depression and anxiety were modified and administered on a daily and weekly basis. Again, there was a statistically significant negative correlation between individuals experiencing depressive symptoms and travel radius (Faherty et al., 2017). Another recent study, Bourla et al. 2018 showed how call logs could be used in combination with GPS sensor information to accurately diagnose depression (Bourla et al., 2018). These studies highlight the potential for using mobility measures from smartphone sensors to aid clinical diagnoses.

DP in Youth with Psychiatric Illness

Although there are a growing number of DP studies examining the adult psychiatric population, very few studies exist in child and adolescent psychiatry.

A recent review by Nisenson et al. identified all currently available studies using DP methodology and showcased the variety of ways passive and active data could be used to better understand disease symptomology and behavior in a population of clinical adolescents (Nisenson et al., Manuscript submitted for publication). There were approximately 26 studies that met the criteria of the review. A few studies using accelerometers and actigraphy were able to measure physical movement and sleep behavior. Sleep time, an important predictor and moderator of treatment outcomes could be inferred through sensors such as the accelerometer. By using DP methodology, temporal resolution was improved, and researchers found that sleep duration and negative affect in youth with anxiety and depression had a bidirectional relationship (Cousins et al., 2011). Other studies analyzed physiological data, e.g., ECG or pulse oximetry. In adolescents with ASD, ECG was used to measure autonomic signals, which correlated with engagement while children underwent a sociological task. With the ability to assess the patient's engagement in real time, a therapist could also personalize the therapy to improve the treatment's efficacy (Di Palma et al., 2017). A few studies showed the power of using sensor data to understand the relationship between children and their environment. Several researchers used GPS location data and census data on neighborhoods that revealed associations between neighborhood disadvantage, substance use, and stress in youth (Mennis et al., 2016).

Adolescence is an important area for investigation because it represents a period of major psycho-developmental and behavior change. The majority of psychiatric disorders begin in adolescence, yet it is also the most understudied population due in part to many studies combining child and adolescent age groups, which unfortunately obscures any meaningful relationships that can be inferred about adolescent-specific outcomes (Paus et al., 2008; Steinbeck et al., 2009). Since adolescence covers a time frame where the capacity to learn is still increasing, clinical interventions during this stage could yield much better outcomes, as new habits can be easier to adopt (Gordon-Larsen et al., 2004). However, many technical and practical challenges prevent more research in adolescents, many of which DP can address.

Difficulty in recruiting adolescent participants represents a significant barrier in adolescent research, particularly for longitudinal studies. Longitudinal studies are valuable for studying disease pathology because they allow researchers to assess the relationship between risk factors and disease onset and examine cause-and-effect. Despite the benefits, longitudinal studies can be many years long and require a significant time commitment from participants (protocols that require subjects to return several times for their assessments). The added complexity of needing parental or guardian consent for adolescent research further contributes to decreased recruitment and retention rates for longitudinal studies (Steinbeck et al., 2009). DP may be a well-suited methodology to address this challenge because it leverages a widely available and accessible technology and reduces the participant burden by allowing assessments to occur remotely (Hsu et al., 2020). For parents and guardians who otherwise would decline consenting to a study because of perceived commitment burdens, remote assessment may make participation more agreeable (Schoeppe et al., 2014). Increasing recruitment numbers and long-term retention may be some of the major benefits of applying DP methodology in adolescent research.

Some of the challenges clinicians face in providing early treatment for adolescents are due to the diagnostic systems, such as the DSM/ICD, which rely strictly upon categorization of mental disorders. While diagnosing adult psychopathologic brings similar challenges, rigid categorical diagnoses may be especially problematic when diagnosing psychiatric illnesses in youth, who often present with significantly different symptoms for the same psychiatric illness in adults (Lilienfeld & Treadway, 2016; Thapar & Riglin, 2020). In an editorial on shaping the future of child and adolescent psychiatry, Skokauskas et al. proposed that the development of new phenotypes and better diagnostic systems might better account for the variation of symptoms between youth with psychiatric illness (Skokauskas et al., 2019). As a digital instrument, DP can generate more comprehensive social and behavioral information, or phenotype, possessing the potential for identifying markers for disease with more granularity than traditional diagnostic tools (Insel, 2017; Waring & Majumder, 2020).

A lack of clinical assessments that accurately reflect the experiences of adolescents is a notable barrier to timely treatment of psychiatric illness, especially for youth with communication difficulties like ASD. Additionally, adolescents tend to have limited insight into their experiences, especially with externalizing disorders (such as opposition, conduct, and attention disorders) (Bein et al., 2015). Self-reports from adolescents suffering from externalizing disorders often require collateral information from parents. For adolescents with internalizing symptoms of depression and anxiety, these symptoms might not be obvious to parents, leading to underreporting and under-recognition of pathology (Choudhury et al., 2003). DP could potentially bridge the gap between the discrepancies in reporting between the youth and their parents by providing objective behavioral information to augment the current assessment protocol. Furthermore, adolescents may be an ideal population for applying DP protocols because of the ease with which they adapt to digital technologies compared with older adult populations (Olson et al., 2011; L. Silver, 2019).

DP utility for Digital Media Use and Mood Assessment

DP may be especially useful for investigating the relationship between adolescent mood symptoms and digital media use. Several studies have already shown promising results using smartphone applications to monitor major depressive symptoms in children and youth. These studies found significant correlations between psychometric mood scores and measured phone usage and physical activity, which demonstrates DP's potential utility for studies exploring adolescent mood symptoms. (Ben-Zeev et al., 2009; Cao et al., 2020; Kauer et al., 2012). Moreover, smartphone developers like Apple have made capturing digital media use metrics, e.g., daily screen time or social media time, readily available to their users to track one's "digital wellness" (Perez, Sarah, 2018). While recent studies have questioned the sole use of screen time metrics for evaluating risks and benefits of digital media use, citing that it is more important to focus on how an adolescent spends their time engaging with digital media rather than on how much total time is spent, DP methodology may be able to bridge that gap (C. L. Odgers & Jensen, 2020). Studies using DP have the additional benefit of capturing other kinds of data such as call logs, text messaging events, screen on and off events and other phone use information which could provide more insight on how adolescents use digital media (Sequeira et al., 2019) Especially during the COVID-19 pandemic where virtual learning has transformed how youth engage in digital technology, DP may be able better discern correlations between digital media use behaviors and mood symptomology in adolescents.

SPECIFIC AIMS

There are limited studies conducted in clinical adolescents using Digital Phenotyping methodology to explore the impacts of digital media use on mood symptoms. This study seeks to address this gap in the literature. The goals of this study are twofold: 1) to describe the relationship between anxiety and depression symptoms and time spent using the smartphone and social media in a sample of adolescents and young adults ages 12-23 and 2) to explore the relationship between anxiety and depression severity and types of most frequently used categories of applications (e.g., social media, gaming or communication).

Based on prior literature, we hypothesize that depression and anxiety severity (measured via PHQ-8 and GAD 7 surveys) is positively correlated with total daily time spent on the smartphone and social media time. We also hypothesize that there will be a significant difference in the distribution of type of media use between individuals with no anxiety or depression levels and those experiencing some threshold of depression and anxiety.

METHODS

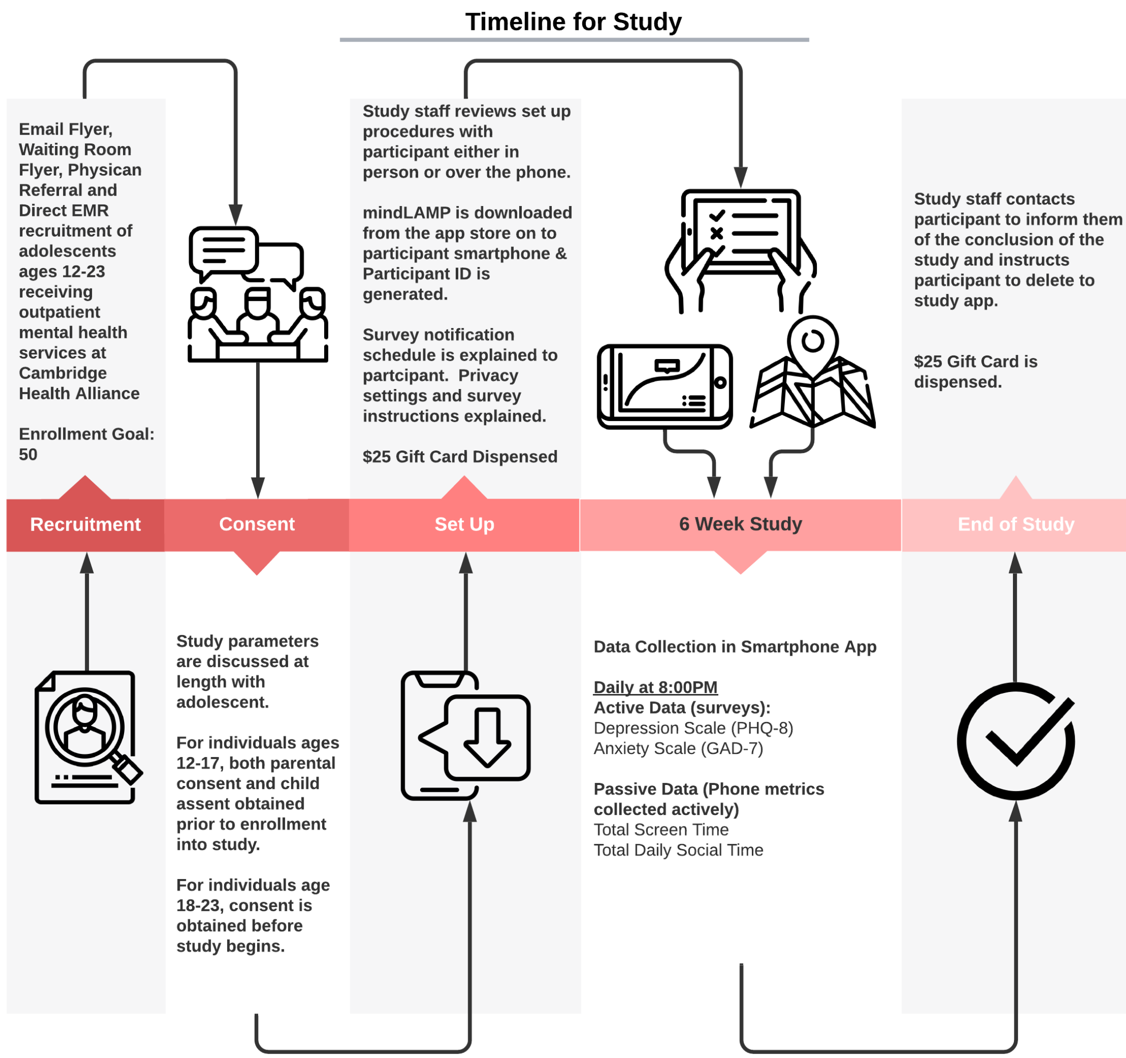

Figure 5. Study Timeline
Timeline from recruitment to the end of the study.

Participants and Recruitment

This study sought to recruit 50 adolescent/young adults between the ages of 12 and 23. The subject number and was determined based on a systematic review of recent studies of adolescent mental health using smartphone apps (Wen et al., 2018). The age range was determined by the increased likelihood of personal smartphone ownership ages 12 and older (Rideout & Robb, 2019b). Participants were screened against the following inclusion criteria: current recipient of outpatient mental health services within a community hospital network in the greater Boston area, owns a smartphone with regular Wi-Fi access, and spoke English. All subjects were provided informed consent, and subjects under 18 were provided parental/guardian consent before participation.

Subjects were excluded from the study if they were unable to speak English, were unwilling to participate in the study, or did not possess a smartphone.

Passive recruitment methods included fliers posted in the child and adult psychiatric outpatient clinic waiting areas at Cambridge Health Alliance (CHA). Clinicians at the site were informed of the study by research staff and asked to refer subjects they felt were suitable for the study. Additionally, potential subjects that matched the inclusion criteria were identified from the child psychiatry clinic schedule within the CHA Electronic Health Records (EHR) system and contacted directly by staff. With the limitations brought forth by the COVID-19 pandemic, the study transitioned primarily to active recruitment from EHR and emailed fliers to potential subjects if emails were listed. Subjects were compensated with a $25 Amazon gift card at the time of joining the study and again for completing the study, for a total of $50.

Study Procedure

The study duration was six weeks. The app mindLAMP (Torous et al., 2019) was used to collect two primary categories of data of interest in this study: active and passive data. MindLAMP is part of the LAMP platform, an open and free tool for research on smartphones (Torous et al., 2019; Rodriguez-Villa et al., 2020; Rauseo-Ricupero and Torous 2021). Subjects were instructed to download the app from the App store (Android or iPhone), assigned their unique participant account, and briefed on the app's features and usage. Notifications were triggered every evening at 8:00 PM to remind the participant of the daily tasks due for completion.

Data collected through the app is uploaded through Wi-Fi, encrypted, and then sent to a secure HIPAA compliant server. No personal identifying information was collected as unique subject IDs were assigned at enrollment. Only study personnel had access to the database portal.

Data Collection and Processing

Data collection was completed using the LAMP platform (Torous et al., 2019). This platform enables researchers to collect active and passive data through the mindLAMP app, view data collection through an online portal, and download data for processing and analysis.

Active Data Collection

The active data collected in our study were comprised of a once-daily survey that contained several sub-surveys. Two sub surveys measured depression and anxiety: an eight-item Patient Health Questionnaire depression scale (PHQ-8), which was modified from the validated diagnostic and severity measure for depressive disorders, PHQ-9 (Kroenke et al., 2009) and the Generalized Anxiety Disorder-7 (GAD-7) (Spitzer et al., 2006). Multiple-choice responses were modified from self-assessment ‘over the last two weeks’ to ‘over the last 24 hours’ to fit the context of daily assessments better. Modification of these scales from their original form for daily administration has not been shown to affect its validity, and the results between the two scales are comparable (Bauer et al., 2018).

Passive Data Collected Actively

Because iPhones have screen time reporting metrics easily accessible to their users, and because this data is separated into social media time and total screen time, we also asked all iPhone users to submit their total daily screen time and social media time.

The iPhone screen time reporting feature also offers the ability to view the top most used apps sorted by the amount of time used. Participants were asked to reference this feature and report the top three applications used that day. The study team further processed the top three applications into categories to characterize the types of applications and their relationship to mood symptoms.

Application Categories Processing

Reported applications were parsed with R Studio using regular expressions. In total, there were 79 unique applications **(See Table 11 in Supplementary).** The study team first searched the Apple app store to determine the category assigned to each application. The "entertainment" category only encompassed "games" and "video streaming" type applications, thus requiring our further parsing into ten major application categories: Communication, Games, Health, News, Productivity, Reading, Shopping, Social Media, and Video Streaming. **Table 12 in Supplementary** shows which category each unique app was placed.

Processing Mood Severity Levels for Comparison of Type of App Used

The daily depression (PHQ-8) and anxiety (GAD-7) scores were averaged for each participant. Using **Table 1**, a severity level was assigned according to their average score using the table (no depression or anxiety, mild, moderate, etc.)

PHQ-8 Score	Severity Level	GAD-7 Score	Severity Level
0-4	No Depression	0-4	No Anxiety
5-9	Mild	5-9	Mild
10-14	Moderate	10-14	Moderate
15-19	Moderately Severe	15 +	Severe
20+	Severe		

Table 1. PHQ-8 and GAD-7 Score Severity Levels
Score thresholds were pulled from the PHQ and GAD-& Instruction Manual (*PHQ and GAD-7 Instruction Manual*, 2010)

We further condensed the level of severity for depression so that instead of five distinct levels, there would instead only be three level: no depression, mild depression and moderate-severe depression. Those with moderate, moderately severe or severe levels of depression were classified as a single level of moderate-severe depression.

We condensed anxiety severity levels from four levels to two distinct levels: no anxiety and anxiety. Individuals who scored anywhere between mild to severe anxiety were classified as having anxiety **(Table 2).**

PHQ-8 Score	Severity Level	GAD-7 Score	Severity Level
0-4	No Depression	0-4	No Anxiety
5-9	Mild	>5	Anxiety
>10	Moderately Severe		

Table 2. Collapsed Anxiety and Depression Severity Levels
Anxiety and depression levels further condensed for comparison against type of apps used.

Data Analysis

Data analysis was performed using the R programming language (v. 4.0.2, https://www.r-project.org) within RStudio (v. 1.3.1056, www.rstudio.com).
The nlme, ggplot2, and sjPlot package in R were used for modeling and plotting. Linear regression models were initially run to visualize the data. Because of the repeated sampling longitudinal structure of the data, multilevel modeling is used. Level 1 represents daily observations for the subject, and Level 2 represents the subjects. Multilevel modeling accounts for the hierarchical data structure and missingness of data. For examining the relationship between mood severity and categories of app use, Chi-square tests were completed.

RESULTS

Relationship Between Screen Time and Anxiety

Linear regressions were conducted to assess the relationship between screen time and anxiety. Because we were using iPhone screen time metrics, only individuals with an iPhone and complete data were included in this sample (n = 37). No significant relationship was found between mean daily screen time and anxiety scores (GAD-7) (p= .28). **(Figure 6)**

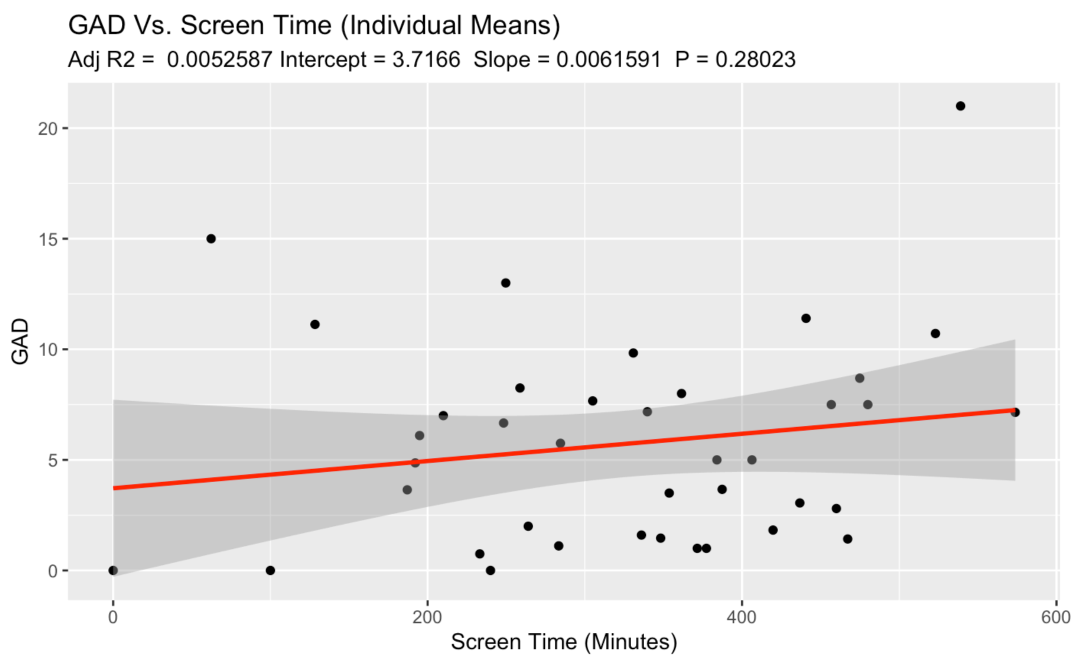

Figure 6: Average Daily Screen Time vs. Average Daily Anxiety Score (GAD-7) Linear regression shows a low correlation between average daily screen time (minutes) and average daily anxiety over six weeks (n = 37). Gray regions indicate a 95% confidence interval.

Multilevel modeling was conducted to account for the nested repeated observations within each subject using the same variables, anxiety, and screen time. This model factored in the missingness of data, allowing more individuals to be included in the sample (n=39). There were no significant relationships found for daily screen time and anxiety scores between subjects (p =.51). **(Table 3)**

	GAD		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	5.52	3.99 – 7.04	**<0.001**
Screen_Time_Min	0.00	-0.00 – 0.00	0.508
Random Effects			
σ^2	11.52		
τ_{00} participant_ID	15.23		
N participant_ID	39		
Observations	333		
Marginal R^2 / Conditional R^2	0.002 / NA		

Table 3: Daily Screen Time vs. Daily Anxiety Score (GAD-7)
Multilevel modeling showing the lack of significant correlation between participant's daily screen time and daily anxiety score (p=.51).

Relationship Between Social Media Time and Anxiety

Linear regressions were conducted to assess the relationship between social media time and anxiety score (GAD-7) (n = 37). No significant relationship was found between mean daily social time and anxiety scores (p= .34) **(Figure 7).**

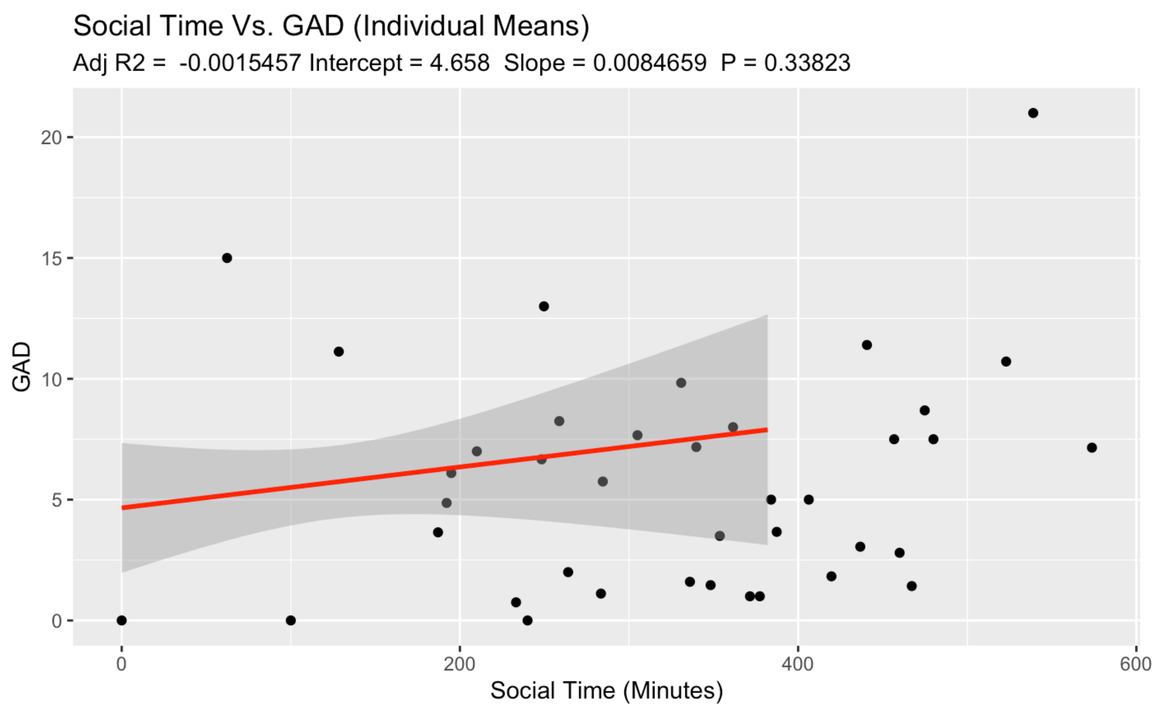

Figure 7: Average Daily Social Media Time vs. Average Daily Anxiety Score (GAD-7)
Linear regression shows a low correlation between average daily social media time (minutes) and average daily anxiety over six weeks (n = 37). Gray regions indicate a 95% confidence interval.

Multilevel modeling was conducted and found no significant relationships for daily social media time and anxiety scores between subjects (p =.98, n=39). **(Table 4)**

	GAD		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	5.75	4.29 – 7.21	**<0.001**
Social_Time_Min	0.00	-0.00 – 0.00	0.980
Random Effects			
σ^2	12.02		
τ_{00} participant_ID	15.42		
N participant_ID	39		
Observations	319		
Marginal R^2 / Conditional R^2	0.000 / NA		

Table 4: Daily Social Media Time vs. Daily Anxiety Score (GAD-7)
Multilevel modeling showing the lack of significant correlation between participant's daily screen time and daily anxiety score (p=.98).

Relationship Between Screen Time and Depression

Linear regressions were conducted to assess the relationship between screen time and depression score (PHQ-8) (n = 37). No significant relationship was found between mean daily social time and depression scores (p= .06) **(Figure 8).**

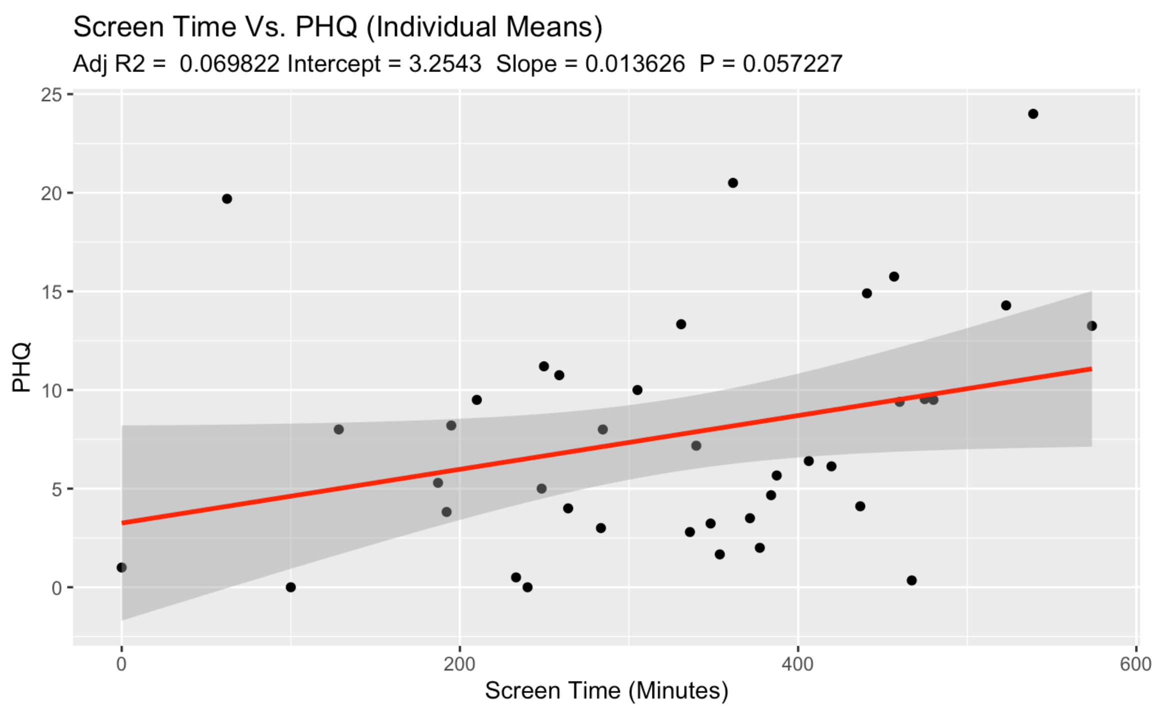

Figure 8: Average Daily Screen Time vs. Average Daily Depression Score (PHQ-8)
Linear regression shows a low correlation between average daily screen time (minutes) and average daily depression score over six weeks (n = 37). Gray regions indicate a 95% confidence interval.

Multilevel modeling was conducted and found no significant relationships for daily screen time and depression scores between subjects (p =.39, n=39). **(Table 5)**

	PHQ		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	7.35	5.44 – 9.26	**<0.001**
Screen_Time_Min	0.00	-0.00 – 0.00	0.392
Random Effects			
σ^2	14.52		
$\tau_{00\ \mathrm{participant\_ID}}$	26.32		
$N_{\mathrm{participant\_ID}}$	39		
Observations	333		
Marginal R^2 / Conditional R^2	0.003 / NA		

Table 5: Daily Screen Time vs. Daily Depression Score (PHQ-8)
Multilevel modeling showing the lack of significant correlation between participant's daily screen time and daily depression score (p=.39).

Relationship Between Social Media Time and Depression

Linear regressions were conducted to assess the relationship between social media time and depression score (PHQ-8) (n = 37). No significant relationship was found between mean daily social media time and depression scores (p= .21). **(Figure 9)**

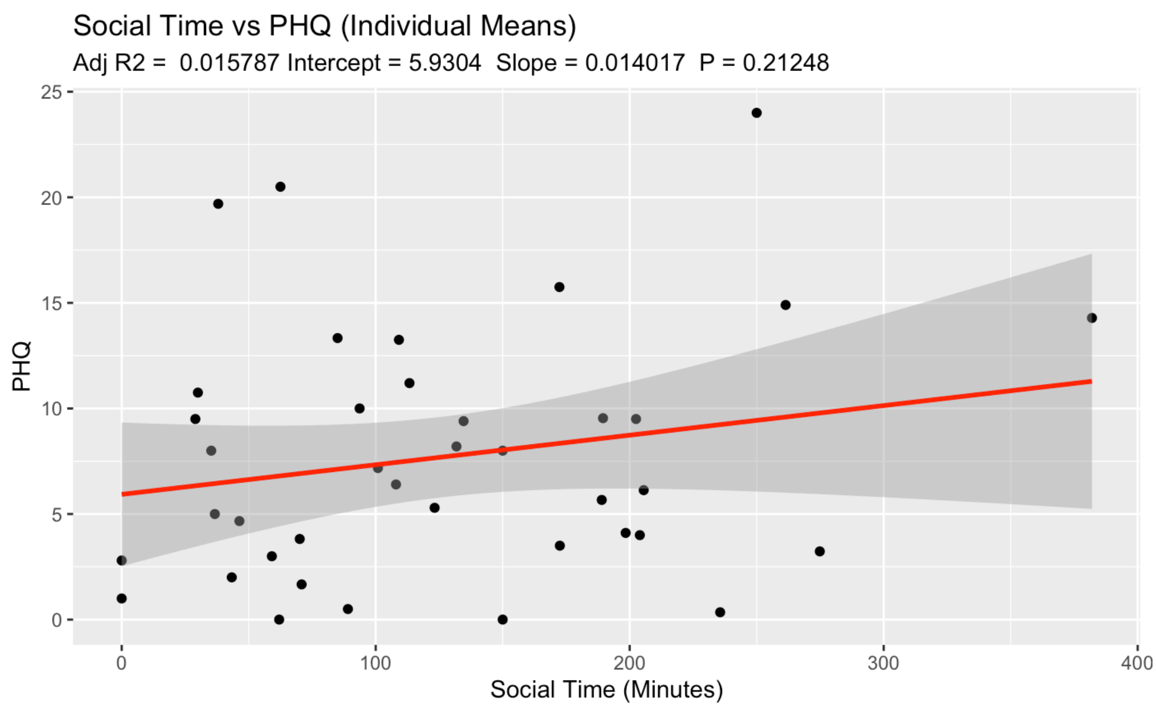

Figure 9: Average Daily Social Media Time vs. Average Daily Depression Score (PHQ-8)
Linear regression shows a low correlation between average daily social media time (minutes) and average daily depression score over six weeks (n = 37). Gray regions indicate a 95% confidence interval.

Multilevel modeling was conducted and found no significant relationships for daily social media time and depression scores between subjects (p =.39, n=39). **(Table 6)**

	PHQ		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	7.42	5.60 – 9.24	**<0.001**
Social_Time_Min	0.00	-0.00 – 0.01	0.365
Random Effects			
σ^2	15.24		
τ_{00} participant_ID	25.75		
N participant_ID	39		
Observations	319		
Marginal R^2 / Conditional R^2	0.005 / NA		

Table 6: Daily Social Media Time vs. Daily Depression Score (PHQ-8)
Multilevel modeling showing the lack of significant correlation between participant's daily social media time and daily depression score (p=.37).

Relationship Between Categories of Top Apps and Depression Severity Level

Daily depression (PHQ-8) scores were averaged for each individual, and thresholds for depression severity were determined based on **Table 1** in the Methods section. The percentage for each category vs. depression severity level is outlined in **Table 7**. Although there seemed to be difference between type of apps used between depression levels, further analysis to normalize the data by condensing severity into fewer levels with Chi-squared revealed that only productivity app use differed significantly between those with no depression and those with moderately-severe depression,

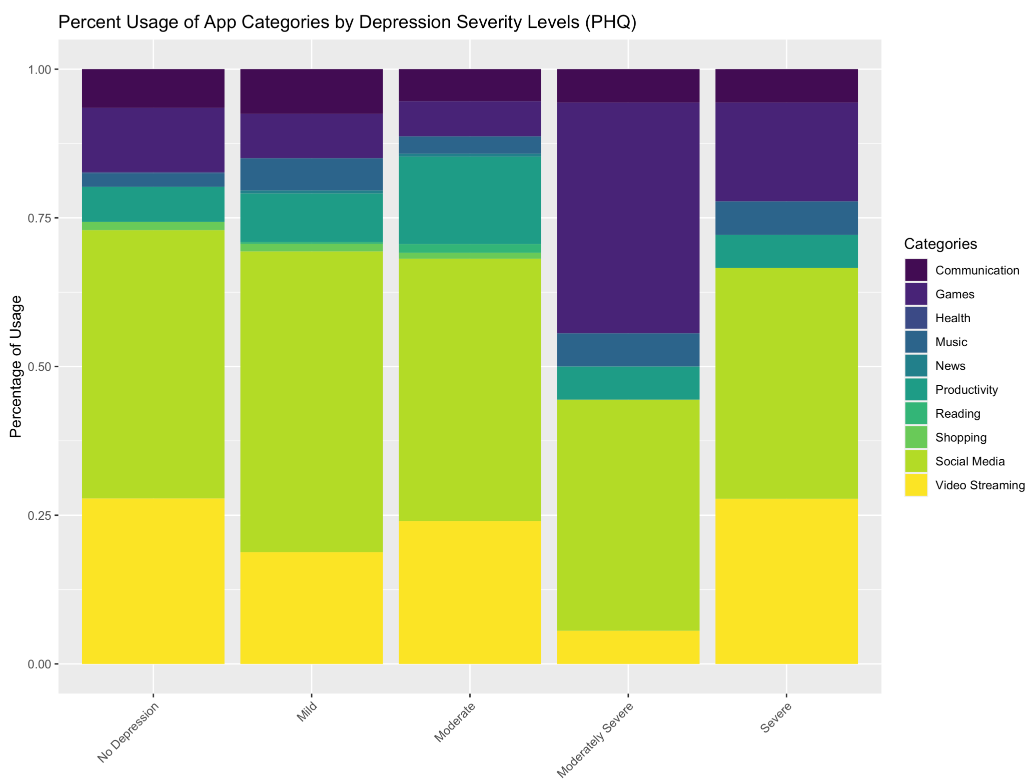

Figure 10: Percentage of Usage of App Category by Depression Severity Level
Bar chart showing the percentage distribution of use in each category of application separated by depression severity level.

PHQ Severity	Communication	Games	Health	Music	News	Productivity	Reading	Shopping	Social Media	Video Steaming
No Depression	6.50%	10.80%	0.20%	2.30%	0.00%	5.90%	0.00%	1.40%	45.10%	27.80%
Mild	7.50%	7.50%	0.00%	5.40%	0.50%	8.20%	0.30%	1.30%	50.60%	18.80%
Moderate	5.40%	5.90%	0.00%	2.90%	0.50%	14.70%	1.50%	1.00%	44.10%	24.00%
Moderately Severe	5.60%	38.90%	0.00%	5.60%	0.00%	5.60%	0.00%	0.00%	38.90%	5.60%
Severe	5.60%	16.70%	0.00%	5.60%	0.00%	5.60%	0.00%	0.00%	38.90%	27.80%

Table 7: PHQ Severity and Percentage of Use by Category
The table shows the percent distribution of app category usage per depression severity level.

Chi-Square tests were performed to determine if there was a difference in the use of the category of apps between those who had no depression and those with mild or moderately-severe depression. It revealed that most categories of app use did not differ significantly between levels of severity, between no depression and moderately severe, except for Productivity apps, $X^2 (1, N= 33) = 4.95$, $p < .01$.**(Table 8)**

Games	Yes App	No App
Mild Depression	4	12
No Depression	10	8
X-squared = 3.2651, df = 1, N=34, p-value = 0.07077		
Mod - Severe	6	9
No Depression	10	8
X-squared = 0.79265, df = 1, N=33, p-value = 0.3733		

Video Streaming	Yes App	No App
Mild Depression	11	5
No Depression	12	6
X-squared = 0.016798, df = 1, N=34, p-value = 0.8969		
Mod - Severe	8	7
No Depression	12	6
X-squared = 0.60923, df = 1, N=33, p-value = 0.4351		

Communication	Yes App	No App
Mild Depression	8	8
No Depression	8	10
X-squared = 0.10494, df = 1, N=34, p-value = 0.746		
Mod - Severe	6	9
No Depression	8	10
X-squared = 0.066165, df = 1, N=33, p-value = 0.797		

Productivity	Yes App	No App
Mild Depression	10	6
No Depression	9	9
X-squared = 0.53684, df = 1, N=34, p-value = 0.4637		
Mod - Severe	2	13
No Depression	9	9
X-squared = 4.95, df = 1, N=33, p-value = 0.02609**		

Social Media	Yes App	No App
Mild Depression	13	3
No Depression	15	3
X-squared = 0.025298, df = 1, N=34, p-value = 0.8736		
Mod - Severe	12	3
No Depression	15	3
X-squared = 0.061111, df = 1, N=33, p-value = 0.8047		

Music	Yes App	No App
Mild Depression	3	13
No Depression	3	15
X-squared = 0.025298, df = 1, N=34, p-value = 0.8736		
Mod - Severe	5	10
No Depression	3	15
X-squared = 1.2375, df = 1, N=33, p-value = 0.266		

Table 8: Chi-Squared Test for Categories and Levels of Depression Severity
There was a significant difference in productivity apps usage between those with no depression and those with a moderate-severe level of depression.

Relationship Between Categories of Top Apps and Anxiety Severity Level

Daily anxiety (GAD-7) scores were averaged for each individual, and thresholds for anxiety severity were determined based on **Table 1** in the Methods section.

The percentage for each category vs. anxiety severity level is outlined in **Table 9**. Although there seemed to be differences between type of apps used and anxiety severity levels, further analysis to normalize the data by condensing anxiety severity to two levels (no anxiety and anxiety) with Chi-squared revealed there were no significance between type of app used between those without anxiety and those with anxiety

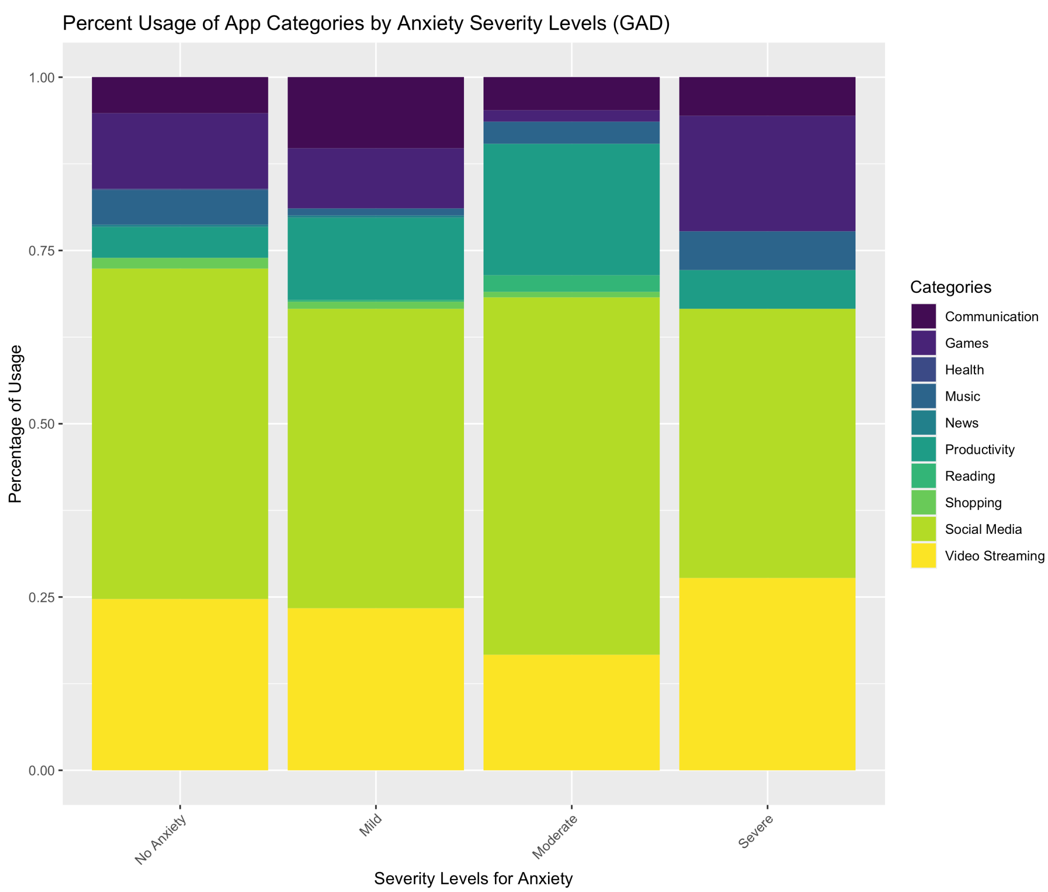

Figure 11: Percentage of Usage of App Category by Anxiety Severity Level
Bar chart showing the percentage distribution of use in each category of application separated by anxiety severity level.

GAD Severity	Communication	Games	Health	Music	News	Productivity	Reading	Shopping	Social Media	Video Steaming
No Anxiety	5.20%	10.90%	0.20%	5.00%	0.30%	4.50%	0.00%	1.50%	47.70%	24.70%
Mild	10.30%	8.70%	0.00%	1.00%	0.30%	11.90%	0.30%	1.00%	43.30%	23.40%
Moderate	4.80%	1.60%	0.00%	3.20%	0.00%	19.00%	2.40%	0.80%	51.60%	16.70%
Severe	5.60%	16.70%	0.00%	5.60%	0.00%	5.60%	0.00%	0.00%	38.90%	27.80%

Table 9: GAD Severity and Percentage of Use by Category
The table shows the percent distribution of app category usage per anxiety severity level.

Chi-Square tests were performed to determine if there was a difference in the use of the category of apps between those who had no anxiety to those who had anxiety. Apps categories with less than five positive responses were removed from the analysis (Shopping, Reading, News, and Health). Anxiety severity levels of mild to severe were clustered into a single anxiety level. The tests revealed that no app category usage differed significantly between those experiencing anxiety and those not experiencing anxiety. **(Table 10)**

Games	Yes App	No App
Anxiety	8	16
No Anxiety	12	12

X-squared = 1.3714, df = 1, N=48, p-value = 0.2416

Video Streaming	Yes App	No App
Anxiety	16	8
No Anxiety	15	9

X-squared = 0.091082, df = 1, N=48 , p-value = 0.7628

Communication	Yes App	No App
Anxiety	12	12
No Anxiety	10	14

X-squared = 0.33566, df = 1, N=48, p-value = 0.5623

Productivity	Yes App	No App
Anxiety	15	9
No Anxiety	11	13

X-squared = 1.3427, df = 1, N=48, p-value = 0.2466

Social Media	Yes App	No App
Anxiety	20	4
No Anxiety	20	4

X-squared = 0, df = 1, N=48, p-value = 1

Music	Yes App	No App
Anxiety	5	19
No Anxiety	6	18

X-squared = 0.11794, df = 1, N=48, p-value = 0.7313

Table 10: Chi-Squared Test for Categories and Levels of Anxiety Severity
There was no significant difference in categories of apps used between those with no anxiety and anxiety.

DISCUSSION

Relationship Between Screen Time and Mood Symptoms

Linear regressions and multilevel modeling did not reveal significant associations between mood symptoms of anxiety ($p = .28$, and $p = .51$) or depression ($p = .06$, and $p = .39$) and daily screen time in our sample. Our results are similar to other recent studies using screen time as a measure of digital media use. A recent large-scale study looking at adolescent mental well-being and digital technology use found that moderate screen time use was not associated with decreased well-being in adolescents, and high screen time engagement had a small negative association (Przybylski & Weinstein, 2017).

The focus on screen time has its roots in studies exploring the impact of television and video game screen times on children's mental health and performance. These studies found that increased screen times led to adverse outcomes such as diminished school performance and increased risk for aggressive behaviors (Keikha et al., 2020; Neuman, 1988). The practical significance of using screen time as a metric for digital engagement today has come to be questioned, as a growing body of research has found primarily small or non-significant associations between screen time and mental well-being (C. L. Odgers & Jensen, 2020).

It may be that the screen time metric is too simplistic to capture the nature of digital devices utilization. The 2020 Common Sense Media report found an increasing percentage of adolescents use digital media for social support and education (C. Odgers & Robb, 2020). Especially following the onset of the COVID-19 pandemic, where learning has moved primarily online, counting the total number of hours spent on a device may not truly capture the nature of device use. Instead, researchers may need to ask how adolescents spend their time online (C. Odgers and Robb 2020). Of note, a recent survey revealed that a majority of teens and young adults utilize digital tools for seeking out health information or peer support, which contribute to more positive outcomes for mental well-being (Rideout, 2018). Total screen time does not fully describe adolescent engagement with digital media and fails to characterize the differences between passive (primarily observational with low engagement: scrolling through social media feeds) and active (learning new topics, content creation or engaging with other users) use. Interestingly, a study focused on the quality of social media use among United States adults found that increased passive social media use was positively associated with depressive symptoms whereas active social media use was negatively associated with depressive symptoms (Escobar-Viera et al., 2018). However, in youth, the relationship between mood symptoms and active versus passive digital media use is more complex. Frison et. al. noted that passive and active use on the social media platform, Facebook, differentially affected male and female depressive mood; females experienced significantly more harmful mood symptoms during passive social media use whereas active social media use positively predicted depressed moods in males(Frison & Eggermont, 2016).

While our findings contradict current intuitions regarding the relationship between screen time and digital media use, it is important not to dismiss the potential impact of digital media based on quality, or type, of use. Future studies using DP methodology may need to consider other methods that can provide more granularity on digital media use behaviors. For example, screen time settings in iOS allow users to view the total daily time spent on each app which can be reported by participants through the research application. Using these reported values, researchers can determine the percentage of time in a day spent on specific categories of apps (social media, video streaming). Additionally, researchers could include daily survey questions that qualitatively capture the active and passive use behaviors to compare to daily mood severity.

Relationship Between Social Media Time and Mood Symptoms

Similar to our findings for screen time effects on mood symptoms, linear regression or multilevel modeling did not show significant associations between reported social media time and depression ($p = .21$, and $p = .39$) and anxiety symptoms ($p = .34$ and, $p = .98$) in our sample. Our results, in part, confirm the findings of a recent study by Kreski et al. that found that social media use was not associated with increased depressive symptoms (Kreski et al., 2021). While many cite cyberbullying and decreased self-esteem as significant negative effects of social media use, recent research suggests that social media may confer protective properties, such as mood improvements through flattering social comparisons (Appel et al., 2016; Twenge et al., 2017). Steinfield et al. found that social media users with lower self-esteem gained more in bridging social capital (connections between individuals across divides in society such as race, class or religion), through social media use than those with higher self-esteem (Steinfield 2008). Although our results challenge the Boers et al. study where anxiety levels correlated with increased social media use in a sample of Canadian adolescents, it is important to distinguish the differences in how mood symptoms were reported within each study (Boers et al., 2020). Using DP methodology, we were able to capture daily mood symptoms. In contrast, Boer's study assessed mood symptoms annually and asked participants to recall significant mood events over 12 months, making their responses vulnerable to memory bias. The application of DP methodology allowed us to capture moment-by-moment experiences, which may offer better sensitivity. Thus, our results may more accurately capture the lived experiences of this population. Our results seem to suggest that overall time spent on social media may not be correlated with increased anxiety or depression symptoms in clinical adolescents.

Relationship Between the Category of Apps Used and Mood Symptoms

Chi-square tests evaluating the difference in frequency in categories of apps used, between those with mood symptoms and those without found that there was no significant difference for the majority of app categories. The only significant difference was seen for productivity apps, where people without depression reported using significantly more productivity apps than those with moderate to severe levels of depression $X^2 (1, N= 33) =4.95$, $p < .0$. This result is interesting because it aligns with the current literature, illustrating that depression is associated with lower productivity and increased difficulty in fulfilling tasks in the work place (Beck et al., 2014; Lerner et al., 2004). Beck et al.'s study, which examined the magnitude of productivity loss to the severity of depression, found that productivity loss could be seen across severity levels, even with those with mild symptoms (Beck et al., 2011). While we did not detect a significant difference in the use of productivity apps between those with no depression and mild depression, these results still signal a behavior difference across more severe levels of depression that should be explored further. It is important to note that capturing app use and assigning their categories may need to be refined and standardized for studies seeking to replicate these findings. Additionally, future studies should consider collecting data on the proportion of time spent on each app compared to the total daily time spent on the device for a more sensitive app usage behavior measure.

Limitations and Challenges

Inclusion and Exclusion Criteria

There are several limitations to this study that should be noted. The study application, mindLAMP, was only compatible with iPhones manufactured in 2015 or later and running on iOS 14; thus, only participants who had access to a late model iPhone could participate in our study. Additionally, the collection of screen time, social media time measures, and top apps data were limited to iPhone users because these metrics were only available on iPhone devices. Although most of our cohort owned iPhones, data from at least five individuals who owned android phones were excluded from the analysis.

Furthermore, the study required that participants be able to read English fluently. Although informed consents were available in Spanish, Haitian Creole, and Portuguese, the study application's daily survey questions and psychometric scales were only available in English. This immediately excluded all individuals who were not able to fluently read and communicate in English. Additionally, it is entirely possible that these constraints on inclusion criteria and study methodology excluded clinical adolescents and young adults from SES disadvantaged backgrounds who may not had access to recent model smartphones. Odgers et al. found that teens from SES disadvantaged backgrounds experienced more negative symptoms from digital media use than those from SES non-disadvantaged backgrounds (C. Odgers, 2018). This may limit how generalizable this study's results are to the population of clinical adolescents across all SES backgrounds.

Future studies using similar applications for data collection should consider designing their application to allow backward compatibility for older smartphone models to address this issue. Similar studies should explore alternative methods for extracting screen use metrics to capture use across users of all smartphone platforms. Lastly, studies could improve their sample by offering translated psychometric scales and surveys to included non-English speaking participants.

Recruitment

There were recruitment challenges that may have impacted protocol adherence and, ultimately, the longitudinal data's robustness. Following the onset of the COVID-19 pandemic, all outpatient visits shifted to telehealth. The ability to reach eligible participants through self-referrals via flyers posted at outpatient waiting areas or by physician referrals was greatly impacted. The study transitioned to primary recruitment through EMR queries of individuals with recent outpatient visits in the department of child psychiatry. Individuals that were potentially eligible for the study were contacted directly by phone. Because most individuals recruited post COVID-19 onset came from direct contact rather than self-referral, participants may have been primarily motivated to enroll because of the study's monetary incentives. While study staff encouraged the participants to continue their adherence to the protocol across the six weeks, and nightly reminders were sent as notifications through the study app, there were still several instances of low compliance to the protocol, which decreased the amount of longitudinal data available for analysis. Although, offering incentives for meeting certain thresholds of completion during the study may address instances of low protocol adherence, this study did not implement this in part because we were still exploring the feasibility of this modality in clinical adolescents. Where a larger sample size could have offset the impact of poor adherence from a few individuals, we were limited by restrictions on recruitment during the pandemic. Future studies may improve study compliance with completion-based incentives and increase sample size and diversity by varying recruitment methods.

Technical Challenges

The study encountered some technical challenges while collecting sensor data with the study app. A majority of the passive data used to infer mobility measures, (significant locations, total home time, location entropy) and device use features (number of sessions, checks, and inferred screen time) relied on sensors such as GPS, accelerometer, and metadata on-screen power state which meant the loss of one or more sensors affected the data for several critical study measures. In a previous feasibility study using the same study app, passive features were successful in continuously collect data (Henson et al., 2020). However, the increased concern for smartphone user privacy over the last few years has led to companies like Apple modifying permission settings for apps that continuously track its users. In the summer of 2020, Apple rolled out a feature that required all apps to ask permission for background operations (O'Flaherty, 2021).

Although this is a promising move forward to protecting user privacy, it has impacted the ability of research apps, like the one used in our study, to collect sensor information reliably. While the study participants were instructed to change the app permissions settings to allow for continuous data collection, the smartphone's privacy feature would often turn back on spontaneously, preventing further data collection. This resulted in inconsistent or missing data streams from GPS and accelerometers throughout the study. Smartphone operating system updates have also affected apps' ability to collect power state information (which is necessary to infer device usage). An interim analysis we completed shortly before these changes showed sufficient passive data collection. However, passive data related to mobility and device use for subjects recruited after the privacy updates were insufficient for processing and therefore were excluded from the analysis.

As applications designed for Digital Phenotyping continue to evolve and mature, so too has smartphone privacy and security. The potential benefits conferred by using DP technology in smartphones, e.g., high-fidelity data, scalable, and accessible across various users, will likely see more roadblocks as time goes on. Until these issues are resolved, researchers should evaluate the feasibility of using DP applications for long-term longitudinal studies. A possible alternative would be to provide participants with a study-standardized smartphone device which eliminates operating system compatibility and sensor issues. However, researchers will need to consider impact of the increased cost and reduced scalability as well as the decreased ecological validity when subjects are asked to carry a study device versus using their own smartphone.

Conclusion

Although a few studies have used the DP methodology to correlate depression and anxiety in children and adolescents, no previous studies have applied DP towards investigating the relationship between digital media use and mood symptoms in a population of clinical adolescents. Because DP methods can collect more objective data through sensors, its application could yield more reliable and accurate results and better depict the behaviors of interest compared to strictly EMA protocols or traditional self-report surveys. Using DP methodology, we found that screen time and social media time were not significantly associated with negative mood symptoms like anxiety or depression. These findings challenge our conventional understanding that digital media use negatively impacts mental well-being in youth. Our review of current literature found a conflicting mix of positive, negative and null associations indicating that the relationship between digital media use and mood symptoms, if there is one, is far more complex. The directionality of this relationship may be obscured by within subject factors such as SES, age or gender.

We saw significantly more use of productivity apps for those without depression symptoms than those with severe to moderate depression in this population of clinical adolescents, reflecting our present knowledge of how depression symptoms can impair productivity. It is clear that DP methodology can assess digital media use behavior and mental health symptoms in clinical adolescents. Future larger-scale studies will need to identify other metrics for digital media use that can better describe how adolescents use their devices. Despite encountering significant technical challenges that affected passive data collection because of emerging security and privacy changes on smartphone devices, DP methodology may still be a powerful tool for building predictive models for early mental health treatment once limitations can be addressed.

SUPPLEMENTARY

2048	8 Ball Pool	Amazon	Among Us	Apple podcast	Bandcamp
3	1	11	3	2	1
Camera	CBS	Choices	Chrome	Clash Royale	Dazzly
3	1	4	9	10	6
Design Home	Discord	Disney +	Dual	Ecosia	Eko
1	13	2	1	1	1
Facebook	FaceTime	Gmail	Goat	Google	Harry Potter
11	2	2	1	5	5
HBO	Hidden Puzzle	Hotel Empire Tycoon	Hulu	iMessage	Indeed Jobs
1	1	2	11	10	1
Libby	Love Island	Mail	Maps	Merge Block	Messages
1	6	1	1	1	34
Monkey	Music	Netflix	NFS Heat Studio	Nike	Notes
1	5	41	1	1	1
Numpuz	Outlook	Photomath	Photos	Pinterest	Pocket World 3D
2	1	1	4	11	1
Pokey Ball	Reddit	Roblox	Safari	Scriptable	SHEIN
2	3	3	32	2	1
SMS	Snapchat	SoundCloud	Spotify	TikTok	Toca Hair Salon
6	109	8	18	63	1
Twitter	Wattpad	Webtoon	WhatsApp	Wordscapes	Yolo
25	2	1	3	4	1
Yubo	Zoom				
1	1				

Table 11. Reported Unique Applications and Their Occurrences

After parsing for unique values, the number of occurrences was tabulated. There was a total of 79 unique apps.

Communication	Games	Health	Music
Facetime	2048	Nike	Bandcamp
iMessage	8 Ball Pool		Apple Music
Messages	Among Us		Sound Cloud
SMS	BitLife		Spotify
WhatsApp	Choices		
	Clash Royal		
	Dazzly		
	Decked		
	Design Home		
	Dual		
	Ecosia		
	Eko		
	Episode		
	Goat		
	Harry Potter		
	Hay Day		
	Hidden Puzzle		
	Hotel Empire Tycoon		
	Love Island		
	Merge Block		
	Monkey		
	Numberzilla		
	Numpuz		
	NFS Heat Studio		
	Pocket World 3D		
	Pokemon Go		
	Pokey Ball		
	Roblox		

Productivity	Reading	Shopping	Social Media
Camera	Libby	Amazon	Discord
Choices	Wattpad	SHEIN	Facebook
Chrome	Webtoon		Instagram
Google			Pinterest
Gmail			Reddit
Indeed Jobs			Snapchat
Mail			TikTok
Maps			Twitter
mindLAMP			Yolo
Notes			Yubo
Outlook			
Photomath			
Photos			
Safari			
Scriptable			
Shutterfly			

Table 12. Applications Sorted by Their Categories

Applications were sorted, and analysis was run after categories replaced the applications in the dataset.

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