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PERSONAL TECHNOLOGY USE, SOCIAL MEDIA, AND DAILY AFFECT IN EMERGING ADULTS

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Abstract

Personal social and communication technology has been widely adopted by the world in the 21st century. With this widespread worldwide adoption, significant controversy exists debating the effects these social technologies have. Specifically, there is a strong debate in the scientific literature over the psychological effects of social technologies, smartphones, and social media usage. Some arguments are made that modern technology can help improve psychological well being, whilst others claim it has destroyed a generation of adolescents and emerging adults. The present thesis aims to address this debate by exploring the current research from a variety of methodologies about social technology usage effects on psychological well-being, including severe discrepancies in survey-based correlational studies, meta-analyses, longitudinal designs, and random assignment experiments. There is also a systematic problem regarding literature in this area, particularly in the validity of self-report measurement instruments in comparison to actuarial assessments of technology use, including screen time. Specifically, there is evidence discussed for systematic overreporting of technology use, in turn leading to false positive, statistically significant results that do not replicate when using actual screen time assessments. This thesis will address these problems in the research literature by using actuarial assessments of screen time in order to see if positive and negative affective variation can be accounted for by utilizing a daily diary methodology.

Keywords: Social technology, well-being, affect, emerging adults, adolescence, measurement, screen time, smartphone, social media

Table of Contents

Tables and Figures

Tables

Figures

Introduction

The History of Technology and Society, with Modern Adoption and Public Opinions Historically speaking, technological innovations have had a large impact on societal trends, social changes, and individual behaviors. When looking at the invention of the telegraph, for example, researchers noticed considerable changes in behavior that bear a striking resemblance to many of the actions committed on the modern day internet (Standage, 2007). Standage argues that the opening of instant, global communication via the telegraph was the initial step that allowed for societal developments that have occurred in the 19th, 20th, and 21st centuries, respectively. Implications could be made that these technological innovations have led to the overall globalization of modern societies, and this trend could continue on into the future. The modern advancements of communication-related technology, including the smartphone and the various infrastructures of the internet, have been widely adopted throughout the world, with public opinion polls showing that an estimated 77% of all adults in the United States owned a smartphone, with over half of smartphone users receiving alerts on their screens (Perrin, 2017). With consistent adoption of these technology in recent generations, the effect of smartphones and social media usage has been questioned, especially for younger cohorts that have always had access to this technology. Specifically regarding young adults, recent public opinion polls not only show steady increases in overall adoption of cellphones and smartphones over the last twenty years, but also that in 2020, 96% of adults aged 18-29 years own a smartphone, whilst 99% own a cellphone at the least; and that out of four different age categories, adults ages 18-29 years have the highest proportion of individuals who are smartphone dependent, compared to other forms of technology and internet access (Pew Research Center, 2020). Roughly 46% of American poll participants report that their smartphone is something they “couldn’t live without”, opposed to the other 54% of respondents selecting the option that it is “not always needed” (Perrin, 2017). Although, there may be some degree of inflation to these public opinion polls from Pew, as they note that individuals who did not respond to the surveys were not included in the dataset, and individuals who do not have access to these technologies may be more difficult to contact for polling data. There may be inconsistencies with how this affects individuals from different cultural and geographic locations as well. Perrin (2019) discussed additional public opinion polling indicating a significant gap in accessibility to a variety of technology in the US, when comparing people from rural versus urban areas, in which 24% of adults living in rural areas reported that internet access was a problem, despite large increases in internet access for rural Americans over time (35% in 2007, to 65% in 2019). In addition, regional differences may not only occur in the US, but also can differ cross-culturally. For example, Jackson & Wang (2013) found that participants from the US considered social networking site use to be more important, and that individuals from the US reported spending more time using these websites than Chinese participants. The authors also indicated the importance of determining how individual personal factors, such as personality, should be considered when predicting use and perceived value of social networking sites, as well as cultural dimensions including individualism and collectivism.

In an influential article published by *The Atlantic*, in 2017 Jean Twenge's writing depicted smartphones as a device that destroyed an entire generation of adolescents. The claims of this piece included trend data depicting teens in this time period were more likely to experience depression the more they spent time looking at their screens; and the release of the iPhone in 2007 corresponded to changes in adolescent behaviors, such as hanging out with friends less, engaging in less dating behaviors, were more likely to feel lonely, and less likely to get enough sleep (Twenge, 2017).

Public opinion polls reflect the sentiments that social technologies are useful, but have negative health consequences. International Pew Research public opinion polls indicate that a large segment of the population say an increasing use of mobile phones has a negative influence on people's physical health (median of 40% between nations). A median 34% of respondents say that mobile phones have had a positive impact on morality, and a large majority of individuals show concern for children being exposed to harmful content via mobile phones (Silver, Smith, Johnson, Jiang, Anderson, & Rainie, 2019). However, these are in opposition to other opinions on smartphones, the same source explains “overwhelming majorities say mobile phones have been more positive than negative for them personally.” Many say mobile phones have a positive impact on the economy, education, and agree that their smartphones “help them to stay in touch with faraway friends and family and keep them informed of the latest news and information.” (Silver et. al, 2019).

Are Social Technologies Good or Bad? An Ongoing Debate

Recently, there have been substantial advancements in technology, especially for technologies used for interpersonal communications, spreading information, and personal entertainment, amongst other functions. With these advancements, significant controversy regarding the impact these technologies have on people, despite widespread acceptance. There have been multiple attempts to study the potential for technology to have psychological impacts, specifically focused on smartphone screen time and social media usage, with varying results. The following portion of this paper will discuss the back-and-forth between researchers in this area, in an assortment of investigative methods they have employed. The present thesis addresses disagreements in the literature on the relationship between technology and psychological well being by employing daily data collection.

Despite the potential for negative, harmful effects of social media, there are some areas in which utilization of these technologies may lead to positive, beneficial, and helpful outcomes. Kaya & Bicen (2016), using general scanning measures of high school students (grades 9-12), found that students tend to reflect their mood on Facebook posts, and comments that are labeled as “nice” are related to the individual’s confidence. In another study, researchers noted that among individuals diagnosed with serious mental illness, greater frequency, intensity, and longevity of social media use, were associated positively with greater civic and community engagement, but social media use was not significantly associated with loneliness, psychiatric symptoms, or quality of life (Brusilovskiy, Townley, Snethen, & Salzer, 2016). Other researchers have further explored this sentiment. For example, Naslund, Aschbrenner, Marsch, Bartels (2016) note that online peer-to-peer connections with individuals suffering from serious mental illnesses improve physical and psychological well-being. In this commentary, the authors implied that when individuals diagnosed with severe mental illnesses connect with peers online, they report benefits including greater social connectedness and learning strategies for coping (Naslund, Aschbrenner, Marsch, Bartels, 2016). Berry, Lobban, Belousov, Emsley, Nenadic, and Bucci (2017) used a creative design in which they thematically analyzed tweets regarding online mental health discussions with the hashtag "#WhyWeTweetMH", in attempts to further understand the reasons for discussion of the topic on the popular online blogging and social media platform, Twitter; the results displayed that the majority of tweets contained overarching themes of (1) sense of community, (2) raising awareness and combatting stigma, (3) safe space for expression, and (4) coping and empowerment. This further pushes for the narrative that social media can be used in order to help cope with a variety of psychological disorders through social connections, online communities, and social interactions with similar others. One literature review of adolescents' social media use and connectedness research noted a pattern of a paradox: social media platforms can create a source of isolation and exclusion; however, these mediums may also increase the ease and accessibility of creating and joining online communities (Allen, Ryan, Gray, McInerney, & Waters, 2014).

In order to be contextually sensitive, I should address the current COVID-19 crisis, as it is possible to have altered many perceptions on social technology. For example, the American Psychological Association released guidelines in March of 2020 explicitly mentioning the use of social media platforms, in addition to text messaging and phone calls, as a means to help stay connected with others socially, without increasing individual risk of contracting the virus (APA, 2020). Wiederhold (2020) notes that while many aspects of social media use are under scrutiny, the platforms could be helpful to reduce anxiety and loneliness, as well as maintaining social networks, in the pandemic. In the current context of the United States, in addition to the widespread adoption and controversies surrounding a variety of technological devices, discussions exist regarding the use of social media as a means of coping, interpersonally communicating, and passing time during the COVID-19 pandemic. However, clinically and empirically, the true psychological effects of the personal use of social technologies is undecided. This thesis addresses the current state of the science regarding the psychological effects attuned with psychological well-being as they are related to the individual, personal usage and screen time spent on smartphones, particularly social media.

As argued below, each of the methodologies used to study the psychological effects of social technologies suffer from a number of limitations. These limitations are discussed in detail with specific examples for each methodology. The research types critiqued in this review include survey, meta-analysis, longitudinal, and experimental designs. Each have specific benefits and limits. Surveys allow for large, standardized participant pools to be exploited with little concern for external validity. Meta-analyses synthesize bodies of research of particular subjects or methodologies for conclusive evidence but often exclude relevant findings (Wely, 2014). Longitudinal research tracks changes over time, exhibiting temporal precedence without establishing causality. There is a more important problem that systematically effects the outcomes of each methodology type in this research area. The most consistent critique involves self-report assessments of the predictor (smartphone screen time and social media use) in this relationship, where individuals are consistently dishonest about their use when compared to actuarial measurements of technology use.

Prominent Research Methodologies and Limitations

Survey-Based research

The following section discusses the current science regarding the negative psychological factors related to technology use in survey data. Among young people, a large number of studies regarding the psychological impact of technology use, smartphone screen time, and social media use, have used survey as their primary method of data collection. Surveys, particularly online surveys, not only provide quick and convenient access to very large pools of data (which in turn leads to higher powered results), but in this area they access individuals that use social technologies. In one study, results from an online survey of 300 university students found a zero order correlation between the risk of smartphone addiction and satisfaction with life, smartphone addiction risk was also positively associated with perceived stress, and negatively associated with academic performance (Samaha & Hawi, 2016). However, the authors also noted that stress partially mediates the relationship between smartphone addiction risk and satisfaction with life, and academic performance mediates the relationship between smartphone addiction risk and satisfaction with life (Samaha & Hawi, 2016). In another study aimed to validate a measurement instrument of problematic social media use, researchers found that scores on their self-report Social Media Disorder Scale (Note: this is not a recognized disorder from the DSM [American Psychiatric Association, 2013], only the name of a scale for research purposes) showed statistically significant, medium, positive correlations with depression, attention deficits, and frequency of social media use and posts in a sample of Dutch 10-17 year-olds, (Eijnden, Lemmens, & Valkenburg, 2016).

However, other survey-based studies attempted to specify the relationship. One study of a nationally representative U.S. sample (N = 1787, ages 19-32 years of age) depicts evidence that having more social media accounts is associated with increased symptoms of depression and anxiety in this emerging to middle adulthood cohort, even after controlling for total self-reported time spent on social media (Primack et. al, 2017). Conversely, some research has looked at the relationship differently. In a nationally representative sample (N = 1749), one study attempted to identify problematic social media use, rather than merely time spent on social media, as being associated with depression symptoms (Shensa et al., 2017). Results implied that problematic social media use, including frequency of use and addictive behaviors, were more strongly associated with depression than time spent using social media (Shensa et al., 2017). The evidence suggests that the way people use social media, not just how much time they spend using social media, is more predictive of depression than time spent on social media alone (Shensa et al., 2017).

While individual survey findings are useful, meta-analyses of similar-type surveys can be used to explore more generalizable and consistent findings. In terms of the survey literature on the relationship between smartphone/social media use and psychological outcomes, multiple meta-analyses have been conducted, and are discussed below. One meta-analysis of 65 peer reviewed studies on Facebook use and mental health suggested Facebook use is related to the following domains: Facebook addiction, anxiety, depression, body image, disordered eating, drinking cognitions, alcohol use and other mental health problems (Frost & Rickwood, 2017). However, the authors noted that the strength and validity of these relationships varied considerably, indicating that overall Facebook use was not necessarily indicative of mental health outcomes, but rather Facebook and social media use in general is multidimensional (Frost & Rickwood, 2017). Another review examined this topic specifically for young people, analyzing 12 cross-sectional designs, looking at findings regarding adolescents' time spent on social media, social media activity, social media investment, and social media addiction (Keles, McCrae, & Grealish, 2019). The authors noted that all domains were related to depression, anxiety, and psychological distress; they also cited methodological limitations, problems with sampling and measurement, suggesting that qualitative inquiry and longitudinal cohort studies would be more appropriate for studying the influences of social media on psychological outcomes in young people (Keles, McCrae, & Grealish, 2019). Since these methodological limitations were cited in this section, the following section addressed this by exploring the research regarding higher quality data in longitudinal research designs.

Longitudinal Research

Although cross-sectional surveys are convenient methods of sampling large groups, one of the disadvantages of this approach is that there is no accounting for temporal precedence. That is, such studies do not account for changes over time. Longitudinal research could reveal whether or not changes in social media and smartphone use over time is related to psychological outcomes. Throughout this literature, a variety of time lengths were used with similar designs. In one longitudinal study involving groups of 594 adolescents' (assessed annually for 2 years) and 1,132 university students' (assessed annually for 6 years) assessments of social media use and depression symptoms, the results indicated no significant predictive ability of social media use to depression symptoms (Heffer, Good, Daly, Macdonell, & Willoughby, 2019). However, greater depressive symptoms predicted increased social media use among adolescent girls (Heffer, et al., 2019). Another study looked at 14-day ecological momentary assessments via cell phones of 388 adolescents, and results provided evidence that adolescents' time 1 (T1) technology use did not predict mental health symptoms at following timepoints, that adolescents' reported mental health symptoms were not worsened in relation to technology use (Jensen, George, Russell, & Odgers, 2019). Opposing the previously mentioned claims from Twenge et al., 2018 that social media use and smartphones have destroyed a generation, one study conducted an 8-year, annually assessed longitudinal design that looked into social media use and its' impact on adolescents and young adults in terms of intra-individual reports of depression and anxiety (Coyne, Rogers, Zurcher, Stockdale, & Booth, 2020). The results showed no such association of increased time spent on social media with depression and anxiety, among 500 adolescents and emerging adults (ages 13-20 years; see Coyne et al., 2020). While longitudinal research can display temporal precedence, this alone cannot infer causal relationships. The following section examined the experimental designs that tried to explore a causal relationship.

Experimental Studies

The literature on social technologies is severely lacking in terms of experimental research; most findings in this field are correlational and predictive at best. The majority of findings on this topic purely present associations, and do not ascertain the potential causal nature of said associations. However, there have been some attempts to apply the experimental process. One recent study was a randomized controlled trial, in which the experimental manipulation involved reduction of Facebook use for 20 minutes daily for two weeks, whilst the control group used Facebook as typical (Brailovskaia, Ströse, Schillack, & Margraf, 2020). With measurements at five different timepoints, results showed that reducing Facebook use was associated with an increased life satisfaction, significantly decreased depressive symptoms, slight increases in the frequency of physical activity, and decreased daily use of cigarettes (Brailovskaia et al., 2020). In a similar experiment, groups were randomly assigned to either not use Facebook for 1 week in the (experimental), or to keep using Facebook as usual for one week (control; total N = 1095). Results showed positive effects of quitting Facebook: increases of life satisfaction and more positive emotions (Tromholdt, 2016). These improvements in well-being attained from quitting Facebook were especially applicable for heavy Facebook users, passive Facebook users, and individuals who report being envious of others whilst using Facebook (Tromholt, 2016).

However, experimental research regarding the psychological impact of social media use has provided inconclusive findings. One study attempted to engage in experimental manipulation by randomly assigning 78 participants from a university in the United Arab Emirates (ages 18-27 years) to one of two groups: an experimental group that abstained from social media for 7 days, with the control group instructed to continue on their regular social media habits (Vally & D'souza, 2019). Contrary to many of the findings from other studies indicating negative effects of social media screen time, the results indicate that those in the social media abstinent experimental condition showed a decline in life satisfaction, increased negative affect, increased loneliness, and no significant difference in stress, when compared to the control condition (Vally & D'souza, 2019).

Self-Report Measurements versus Actual Screen Time

Much of the research discussed above include the use of self-report measurements for technology use habits One major flaw in this entire subfield of the relationship between social technologies and psychological factors is this reliance on self-report measurements. This issue involves a problem with measurement: self-report measurements and actuarial assessments of screen time are not equivalent. Junco (2013) investigated external validity of self-reported Facebook use, finding that while self-report use does technically positively correlate to actual use, the participants averaged 26 minutes a day (SD = 30) on Facebook, but reported an average of 145 minutes per day (SD = 111), indicating systematic over-reporting of actual time spent using the website, with extremely wide standard deviation.

Other researchers in review of measurements of engaging in social networking sites (SNS) have noted an important concern for the measurement validity, and suggested they be validated by comparison to data collected from other methods, such as data mining, to account for recall bias (Sigerson & Cheng, 2018). Scharkow, (2016) attempted to validate self-report measures of internet time use in comparison to client log files, results showed the accuracy of self-report data is low, and these deviations are not merely random. Rather, the authors claim there are systematic patterns of misreporting and over-reporting of use; however, they also observed the reporting of specific content was more accurate than overall general use (Scharkow, 2016). In addition to screen time, there are other areas of self-reported smartphone use that involves serious inaccuracies. One study looked to compare actual smartphone use to the Mobile Phone Problem Use Scale over 2 weeks, and found that the often cited and empirically supported scale did not correlate to any measure of smartphone use, including self-report estimates as well as actuarial data (Andrews, Ellis, Shaw, & Piwek, 2015). The key finding this study noted was that neither estimated duration, nor estimated number of uses per day correlated with the Mobile Phone Problem Use Scale, and the estimates did not correlate with actual smartphone use, regardless if the measurement was time spent or frequency (Andrews et al., 2015). However, it should be noted that this study had a very small sample size of only 23 participants, which may have influenced the results (Andrews et al., 2015).

The problem of overreporting not only is a measurement error in and of itself, but also becomes an issue in addressing the predictive ability of this measurement, particularly in the ability to predict psychological outcomes. One group of researchers looked into various modalities of measuring smartphone use via screen time and self-report scales that are empirically supported; the results showed that using self-report instruments instead of objective screen time measurements drastically inflates the effect size of the relationship between smartphone use and mental health symptomologies, including tripling and even quadrupling the size of the relationships (Shaw, Ellis, Geyer, Davidson, Ziegler, & Smith, 2020). Similar findings have been noted in another study looking at this topic, specifically results showing that among a sample of 393 iPhone users using Apple's "Screen Time" feature, that participants not only misestimate weekly overall iPhone usage by 22.1 hours and weekly social media usage by 16.6 hours; but also correlations between estimated use and well-being were consistently stronger than correlations between actual use and well-being, and the amount of inaccuracy in estimated use is related to levels of individual well-being (Sewall, Rosen, & Bear, 2019). The effects that this measurement error have are not discriminatory; even the previously mentioned experiments used self-report measures of Facebook use (Tromholt, 2016), which effectively nullifies or reduces the effect of the findings of the experiments due to exaggerated self-reports of use. This measurement error leads to statistically significant findings in analyses that likely would be non significant, had they used a more accurate measure of time spent on these platforms (Shaw et al., 2020).

In this study, a daily diary approach was used. Daily diary methodology, broadly speaking, is a type of assessment that involves individual subjects reporting data at least once per day, every single day, for a given period of time (Lischetzke, 2014). This methodology falls under the broader category of ecological momentary assessment, and is used to account for individual experiences within their environment, patterns of within-subject fluctuations on measure constructs between timepoints, and processes that occur over time between participants

(Lischetzke, 2014). In one example of a daily diary smartphone study conducted on individuals who have survived a suicide attempt, researchers noted that over the course of 28 days, daily changes in protective factors for suicide risk, such as perceived social support, predicted overall suicidal ideation, but not daily changes in suicidal ideation (Coppersmith, Kleiman, Glenn, Millner, & Nock, 2019). Due to the daily diary format, the researchers were able to infer that perceived social support can display strong variability over the course of time, and that social support is a protective factor that varies over time (Coppersmith, Kleiman, Glenn, Millner, & Nock, 2019). Since daily diary studies are able to infer larger trends of constructs that can change over periods of time, this format was used in the present study.

The Present Study

So far, the varying sources that describe our modern relationship with social technologies were discussed. Much previous research has not reached consensus, regardless of methodology. Aforementioned surveys, longitudinal studies, and even experiments all have mixed results, some showing statistically significant relationships between smartphone and social media use and psychological well-being outcomes, whilst others have not shown similar results. The particular issue present in this research is that self-report measurements have been used most often, instead of actuarial assessments of individual technology use, like screen time. There is substantial, published research previously mentioned showing systematic problems with over reporting on self-report measures, leading to inappropriate statistical significance. The current state of the literature shows a specific problem, in which actuarial measurements of screen time have seldom been used to study technology use and psychological outcomes. This thesis aimed to address this gap, by designing a study in which users will report their actual screen time (for both overall smartphone use, as well as use of social media applications specifically) in addition to reporting their daily positive and negative affect. Analyses were conducted in order to see if there is a relationship and the direction of the relationship, between social technology use and daily affective variation. For the purposes of this study, social technology was operationally defined as the use of social and interpersonal communication technological services that are utilized by portable, handheld, smartphones that have access to internet connections.

In this study, the predictor variables included smartphone screen time (overall) and screen time spent on social media applications. The outcome variables included positive affect, negative affect, and sleep. The following (nondirectional) hypotheses are proposed:

- Hypothesis #1: Daily screen time will be associated with psychological well-being
    - Hypothesis 1A: Daily screen time will be associated with daily positive affect
    - Hypothesis 1B: Daily screen time will be associated with daily negative affect
    - Hypothesis 1C: Daily screen time will be negatively associated with daily sleep factors
- • Hypothesis #2: Daily social media use will be associated with psychological well-being
    - Hypothesis 2A: Daily social media use will be associated with daily positive affect
    - ○ Hypothesis 2B: Daily social media use will be associated with daily negative affect
    - ○ Hypothesis 2C: Daily social media use will be negatively associated with daily sleep factors

Method

Procedure

Participants were recruited through an online system that awarded them with class credit for participation in the study (SONA), and were given instructions over how to take part in the study. These instructions included checking an application on their smartphones that was designed to track their daily amount of screen time, as well as the proportions of what applications they spent the most time using. Participants were also informed that in order to receive full credit for participation, they must complete a brief questionnaire asking about positive and negative moods, as well as sleep quality, each day for seven consecutive days. Participants were informed that credit was granted for each day of participation, with the maximum credit being granted for completing the survey each of the seven days.

Part 1

The study began with the participants signing up online in order to receive credit, and initially completing a survey that provided instructions for the daily diary format, asked for various demographic characteristics such as year in college, race, ethnicity, sexual orientation, sex, and age. Participants had to provide a 5 digit, unidentifiable SONA ID number in order to receive credit and be included in the analyses. At the end of the survey, participants were provided with a link to a separate Google form to enter their cellphone number, with an explanation that this would be used to send the survey link for the daily diary. This separate Google form was used in order to keep the participants' cell phone numbers separate from any identifying information. The phone numbers were used to send a text message to the individual participants via a scheduled texting service, EZ Texting. The EZ Texting services was tested by the researcher before any data collection began.

Part 2

The second part of the study included the daily diary survey. This survey was sent to the cell phone numbers that participants provided in the Google form at the end of part 1. The survey links were sent via text message, every day at 5pm, for seven consecutive days, following the day the participant signed up for the study and completed part 1. The justification for the time of day for sending the survey was that this would likely be a time that most college students would not be in class, and therefore could see the message and complete the survey. Each text message sent to participants included only a link to the survey initially. Due to a lack of participant engagement in completing consecutive days of the survey, an IRB amendment was filed and approved in order to add more to the text messages. Specifically, the message was “Please remember to fill out your daily diary study at http://lyceu.me/SmartphoneStudy for additional SONA credit STOP to end.” Participants who replied to the text with “STOP” did not receive additional text messages beyond that point. Participants had to provide a 5 digit, unidentifiable SONA ID number in order to receive credit for each day of participation, and be included in the analyses.

Data was stored in three separated databases; one database for the responses from part 1, one database that only included cellphone numbers and no other information, and one database that included the responses from part 2.

For the purpose of analyzing daily variation in mental health, daily affect was used to represent constructs of positive psychological well-being, and mental health outcomes. Affect has previously shown to fluctuate through the course of cognitive behavioral therapy, in that clients experience higher positive affect and lower negative affect over the course of treatment, including significant shifts in affective personality regardless of the client’s individual problem (Saxon, Henriksson, Kvarnström, & Hiltunen, 2017). Affect has shown to be predictive of state anxiety, depression, general psychological dysfunction, with correlations to both positive and negative affect (Watson, Clark, & Tellegen, 1988).

Daily Diary Measures

During the daily diary study, participants were reminded daily to fill out the daily survey. The following components are the parts of the survey completed by participants once per day, during each of the seven days of the study:

Positive and Negative Affect Scale – Short Form (PANAS-SF) (Watson, Clark, & Tellegen, 1988). The PANAS-SF contains 20 adjectives (see TABLE) participants responded with regards to how they felt *at that moment*, using a 5-point scale (1 = *very slightly*, 5 = *very much*). Scale scores for PA (α = .92) and NA (α = .92) were calculated by summing the 10 PA and 10 NA items. This follows the same protocol as previous studies using the PANAS-SF in a daily diary format (Merz & Roesch, 2011), in which trait and state positive affect (PA) and negative affect (NA) were associated with stress, anxiety, and a variety of self-esteem domains. For these purposes, the PANAS-SF was used as a measurement of state, subjective psychological well-being.

The positive and negative affective variables were calculated using the standard format of the measure from previous research, calculating positive affect and negative affect separately for analytics (Watson, Clark, & Tellegen, 1988). Since the items on the PANAS-SF are Likert-style, range from 1-5 for each question, and there are ten questions for both positive and negative affect, respectively, then the individual scores on the PANAS-SF ranged anywhere from a minimum of 10, to a maximum of 50 (Watson, Clark, & Tellegen, 1988). These individual 10-item scores for daily positive and negative affect were used in the analyses. On these measures, higher scores on positive affect indicate higher levels of positive affect, while higher scores on negative affect represent higher levels of negative affect (Watson, Clark, & Tellegen, 1988).

The Pittsburgh Sleep Diary (PghSD) (Monk et al., 1993). The PghDS has been shown to be correlated to circadian type overall subjective sleep quality (Monk et al., 1993). Only one portion of this measure was used in the current study, with 3 individual "sliding" rating scales assessing sleep quality, mood of final wakening, and alertness on final wakening. In addition, other questions were used from this measure, including asking what time participants went to bed last night, minutes until falling asleep after going to bed after turning off lights and screens, and what time they woke up in the morning. Also, two questions were modified from the original PghSD to include screens as a source of light. These were rephrased as follows: "At what time last night did you turn off all your lights and screens?" and "How many minutes passed (after you turned off your lights and screens) until you fell asleep? Use your best guess."

There is some previous evidence that suggests that insufficient sleep in adolescents may be due to increases with new-media screen time (Twenge, Krizan, & Hisler, 2017). In addition, there is previous evidence that sleep disturbance severity is positively related to coexisting psychopathology (Morin & Ware, 1996). Another study noted that individuals that self-reported to have naturally occurring sleep problems showed higher scores on scales measuring somatic complaints, depression, and anxiety, and that frequency of sleep disturbance was related to severity of self reported symptoms (Tkachenko, Olson, Weber, Preer, Gogel, & Killgore, 2014).

Screen time and application usage

Participants were instructed to open their cellphones to a screen time tracker. Participants with Apple's iOS were instructed to open the settings app, and select "Screen time > Toggle the "Share Across Devices Feature to 'Off'" (this prevents smartphone screen time with being aggregated with data from other devices). Participants were then instructed to go to their settings app, "Screen Time > See All Activity > Day" and to report the hours and minutes total for the current day, as well as the hours and minutes listed under "Social Networking". While there are other types of smartphones on the market that do account for significant proportions of the market share, previous research of similar constructs has only been established for iPhones (e.g., Shaw et al., 2020), and among other smartphone operating systems, there are no universal, simple means of attaining screen time data. For the sake of consistency and parsimony, iPhones were the only smartphone operating system used in this study. Many different applications fall under the term of "social media" in Apple's screen time feature. Some of these include, but are not limited to, blogging applications such as Twitter and Tumblr; video and image sharing applications such as Instagram, Snapchat, and TikTok; personal social media applications like Facebook; and messaging applications like GroupMe and Apple's Messages application.

Analyses

The data was analyzed using Generalized Estimating Equations (GEE). GEE is an extension of the General Linear Model that allows for the computation of average estimates of regression parameters across timepoints when there is an unknown correlation between timepoints. Unlike more complicated approaches (e.g., multilevel modeling), GEE does not attempt to model the covariance structure of predictor variables – instead, it removes the influence of the covariance from the computation of the parameter of interest. The resulting output of GEE can be interpreted similarly to a regression. In other words, GEE can be used to determine how much of the proportion of the variance of the outcome variables is accounted for by the variability of the predictor variables. In addition, GEE can utilize missing data points that may be lost due to individual participant attrition over time, including these in the overall analysis. In this case, the variability in daily smartphone screen time and daily social media screen time (between and within participants) was used to predict the variability in the daily measurements of positive affect, negative affect, and sleep factors.

The data was analyzed in R using the *geepack* package. The study was preregistered in the Open Science Foundation registry, meaning that the initial literature review, a priori hypotheses, and analytic plans before any data was collected or any analyses were conducted are viewable at the following web-link: https://osf.io/qrv9n/

Results

Before any analyses were conducted, multiple exclusions were made in the dataset. Some participants completed the survey more than the seven times needed in order to receive credits for participation. For these participants, they were granted full credit for the participation. However, any of the completions of the survey after seven times within an individual participant, were not granted more credit, but were still included in the analyses, as there was no prior plan to remove participants with excessive participation, nor was it expected that participants might complete extraneous surveys. In addition, daily diary survey entries that contained a missing or incomplete SONA ID number at the end of the survey were excluded from the analysis. This is because students who participated are provided a de-identifiable 5-digit SONA-ID used to sign up for and receive credit in participation of psychological research. In this survey, participants had to enter in their SONA ID to indicate that they were consenting to participation in this research. So, participants who did not enter a valid SONA ID number were excluded from the analysis since doing so indicated not consenting to participation in the study.

Many of the variables had to be calculated before the analyses were conducted. For screen time and social media screen time, the participants were asked to report the total number of hours per day in one survey questions, and the total number of minutes in another survey question. This data was converted into a total number of minutes per day in the following manner:

[(hours per day) X 60] + minutes per day = total minutes per day

The variables from the PghSD were a series of specific questions extracted from the measure. These included ratings on a slider scale from 1-100 to indicated the individual participant's perceived sleep quality, mood upon awakening, and alertness upon awakening. The scores from 1-100 were used in the analyses. In addition, other questions used from this measure included asking what time participants went to bed last night, minutes until falling asleep after going to bed after turning off lights and screens, and what time they woke up in the morning. These questions were attempted to be used to calculate a total score for how much sleep the participant reported getting the night before, in hours and minutes. However, due to a wide variety of data included in these questions that did not calculate to actually possible sleep times (i.e. people reporting sleeping for negative numbers of hours/minutes, reporting sleeping for inordinate amounts of time, or not being able to tell if participants were correctly reporting "AM" or "PM"), this was not included in the final analysis.

The sample included students taking the Introduction to Psychology course at Murray State University. These are the descriptors of the sample who completed at least one day of the daily diary study: n = 97, 78 females total, 19 males total, mean age of 19.4 years. The mean number of completed daily diary survey entries was 2.57 days (SD = 3.80, min = 1, max = 30).

This occurred with a total number of 177 daily observations from the sample. More specific information regarding the sample can be seen in Table 1. These values were calculated by taking the mean of each participant's overall responses for each day, and using these daily averages to determine the mean and standard deviation of variable responses throughout the dataset.

Table 1.

Average daily values for Affect, Screen Time, and Social Media Screen Time

Daily Variable	Mean	Standard Deviation
Positive Affect	26.02	9.14
Negative affect	19.13	8.22
Smartphone Screen Time (minutes)	315.73	163.44
Social Media Screen Time (minutes)	178.64	117.93

In this sample, there were some patterns regarding the participant's responses overall. For example, as shown in figure 1, negative affect appeared to generally decrease over time, while positive affect showed considerable variation between timepoints for all participants. These patterns for negative and positive affect can be shown in the top left and top right graphs in figure 1. In addition, there was little evidence indicating any changes over time in the reported amounts of screen time and social media screen time, as displayed in the bottom left and bottom right of Figure 1.

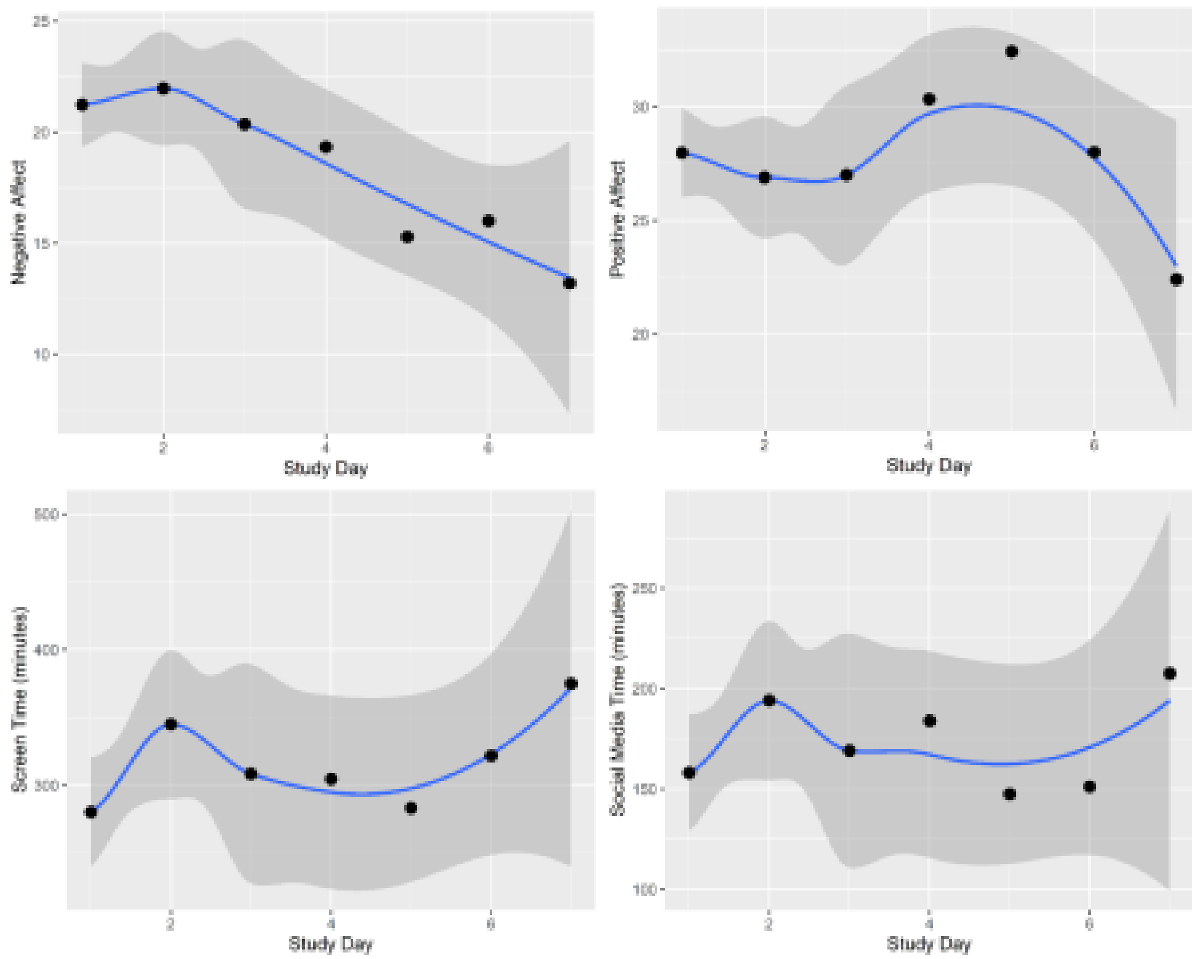
Figure 1

Top Left: Daily averages and standard error margins for Negative Affect over the course of the study

Top Right: Daily averages and standard error margins for Positive Affect over the course of the *study*

Bottom Left: Daily averages and standard error margins for Screen Time over the course of the study

Bottom Right: Daily averages and standard error margins for Social Media Application Screen time over the course of the study



The results of the GEE indicated a variety of different relationships between the predictor variables (screen time and social media screen time) and the outcome variables (sleep factors, positive affect, and negative affect). Specifically, daily iPhone screen time was significantly positively associated with daily negative affect (b = 0.012, SE=0.005, p =0.023). This can be interpreted that for every minute of increase in daily iPhone screen time, there was an increase of 0.012 points on the negative affect scale in the PANAS. In addition, daily screen time spent on social media applications also indicated a statistically significant positive association with daily negative affect (b = 0.016, SE= 0.008, p = 0.045). This can be interpreted that for every minute of increase in daily screen time spent on social media applications, there was an increase of 0.016 points on the negative affect scale in the PANAS. While these relationships are statistically significant (all $p < 0.05$), they may not indicate a very strong relationship (e.g., b = 0.012 for screen time, and b = 0.016 for social media), and some of these associations could be explained by multivariate outliers, or individuals who reported more screen time, social media screen time, and/or negative affect than the vast majority of the rest of the datapoints in the dataset. This can be more clearly seen in figure 2 and figure 3[1], for visualizations of the dataset. One methodological point is the importance of visual inspection of the data, and not merely discussing the statistics of a priori hypotheses testing alone. Visual inquiry of datasets has been stressed by the American Psychological Association Task Force on Statistical Inferences in the past (Wilkinson, 1999), as data visualization can communicate complex information that statistical inferences alone may not exhibit. Upon visual inspection of the data, it can be inferred these relationships are non-linear. Instead, the present data shows a nonlinear pattern.

[1] Visualizations are spaghetti plots, which contain separate lines for each participant. Opaque areas have less variance. The white line indicates the median.

Figure 2

The Relationship between Daily Screen Time Minutes on an iPhone and Negative Affect

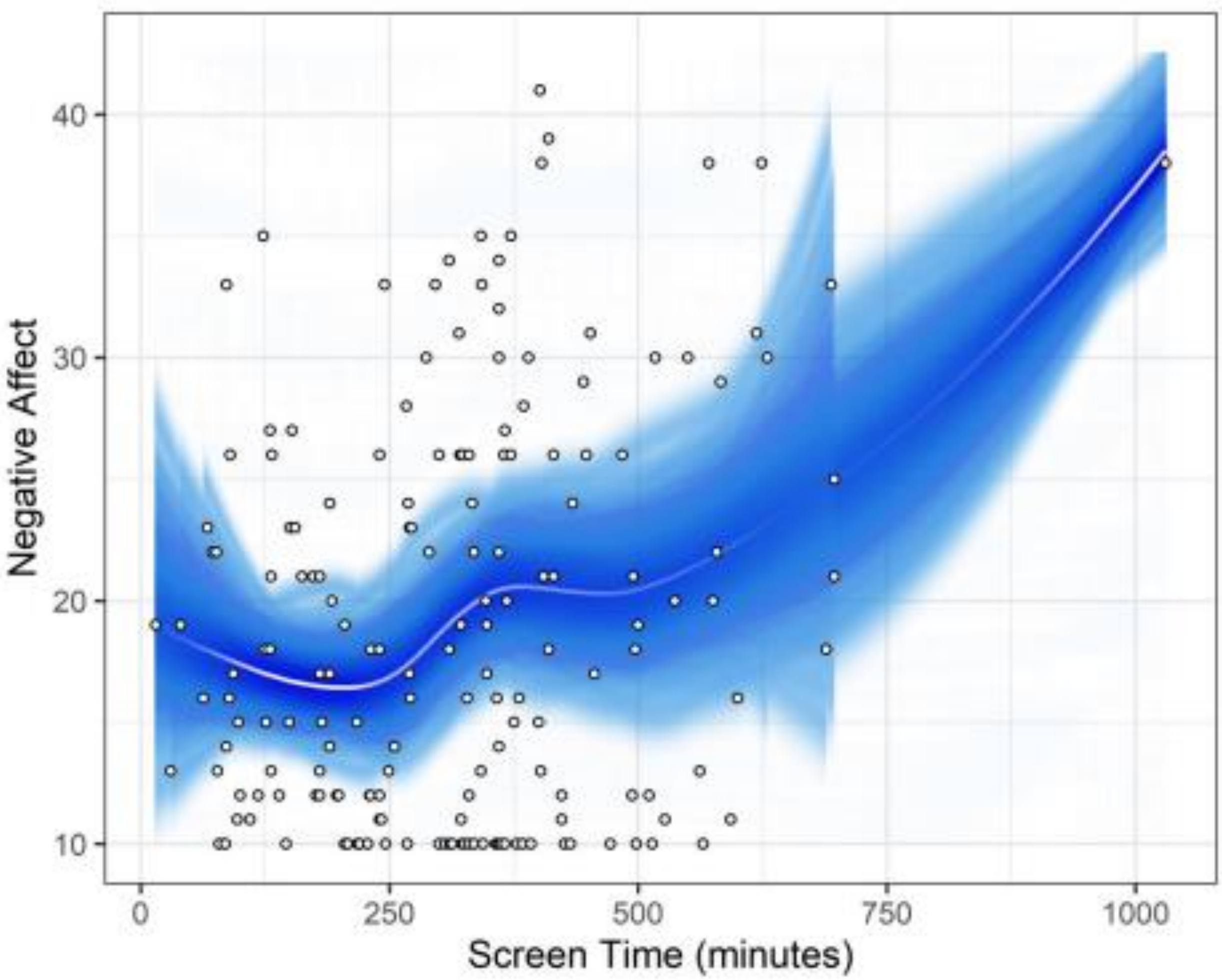
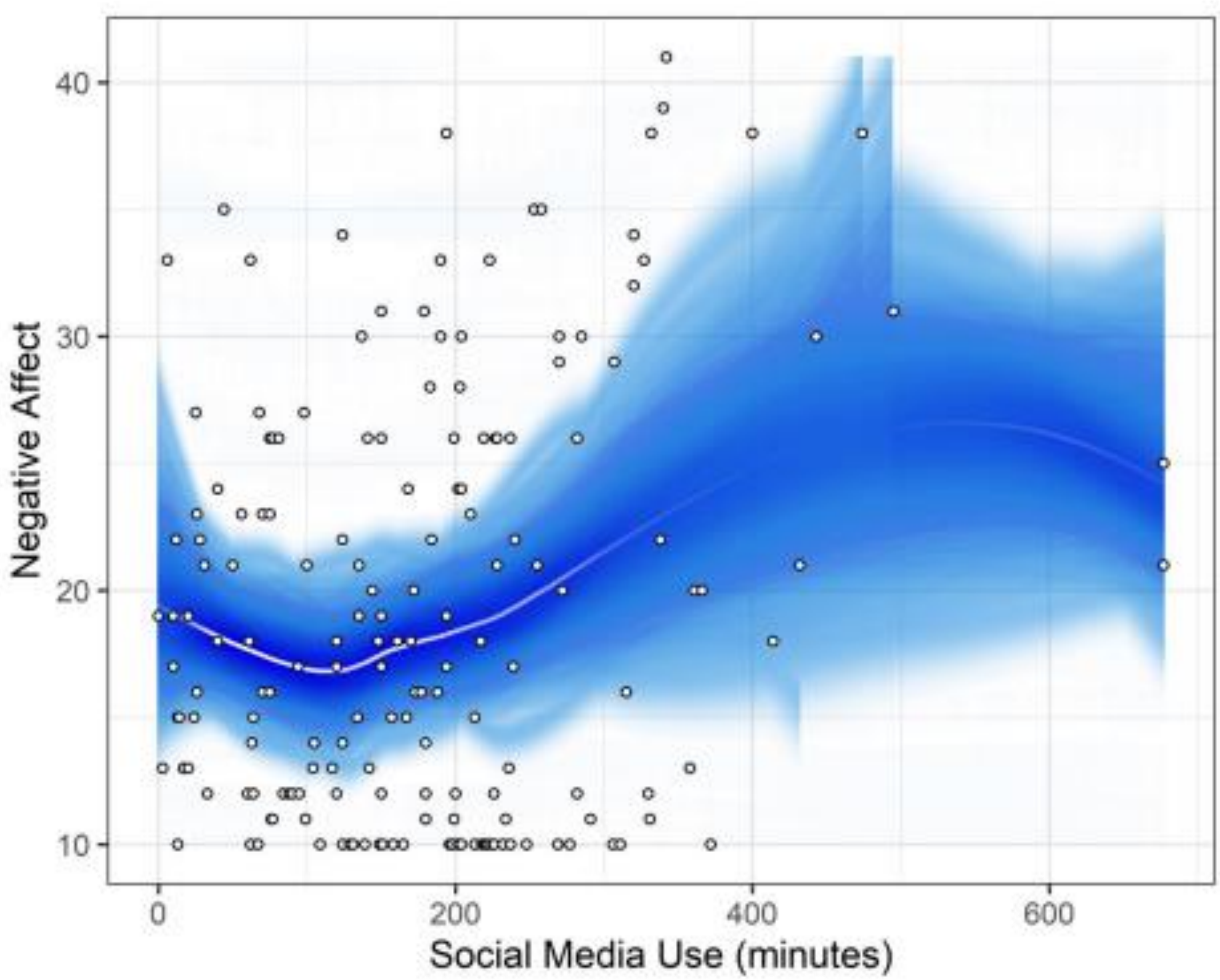


Figure 3

The Relationship between Daily amount of time spent on Social Media applications on an iPhone in minutes, and Negative Affect



Positive Affect

While statistically significant associations were found for negative affect, the same cannot be said for positive affect, or any of the sleep variables. Specifically, daily screen time (b = -0.005, SE=0.006, p = 0.403) and social media screen time (b = -0.011, SE= 0.007, p = 0.13) are not significantly related to positive affect. These relationships can be more clearly seen in the data visualizations in figure 4 and figure 5. Again, the importance of visualization of the data should be stressed as this can more clearly present a picture of the true complexity and nature of the relationship that the statistic alone does not show (Wilkinson, 1999).

Figure 4

The Relationship between Daily Screen Time Minutes on an iPhone and Positive Affect

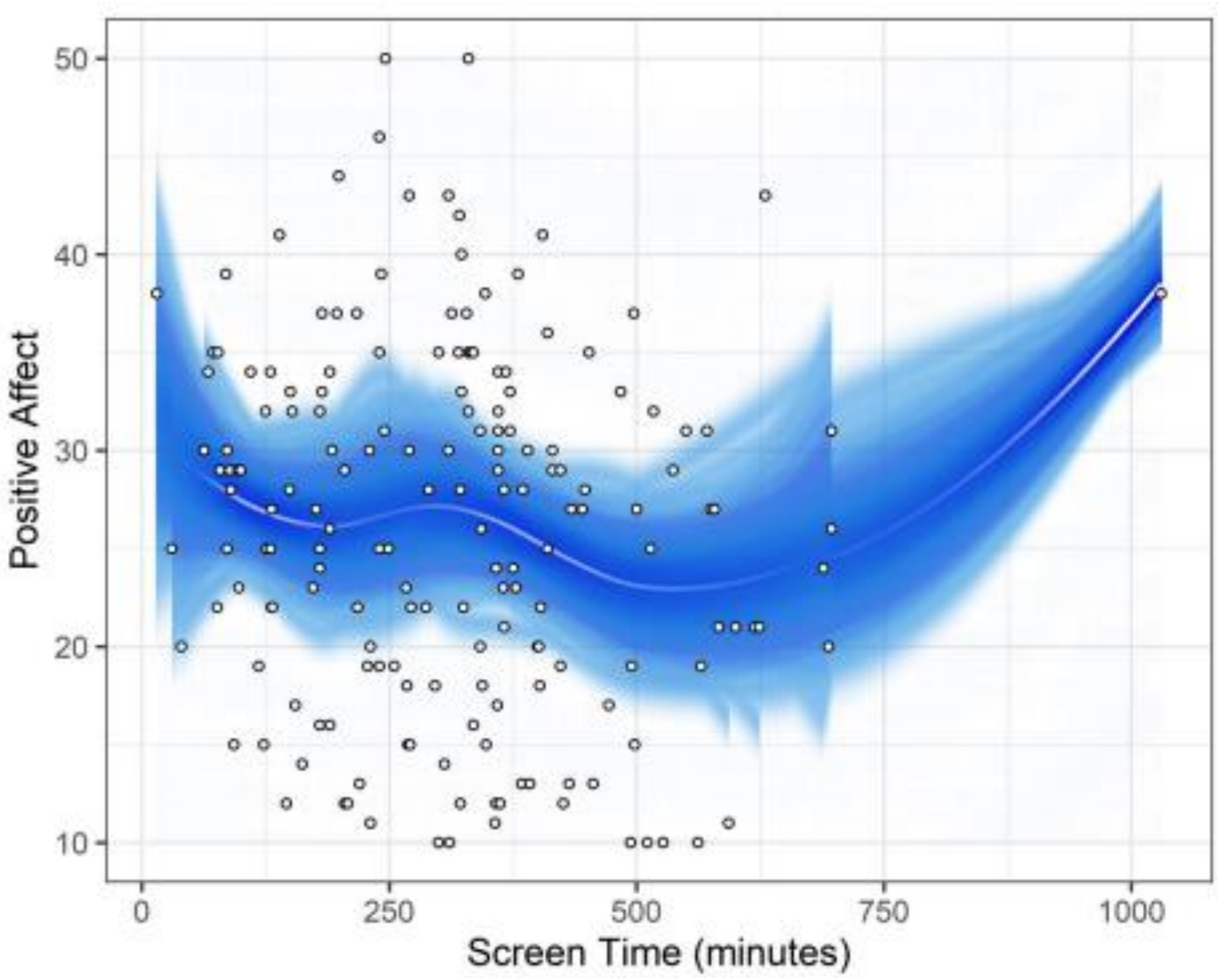
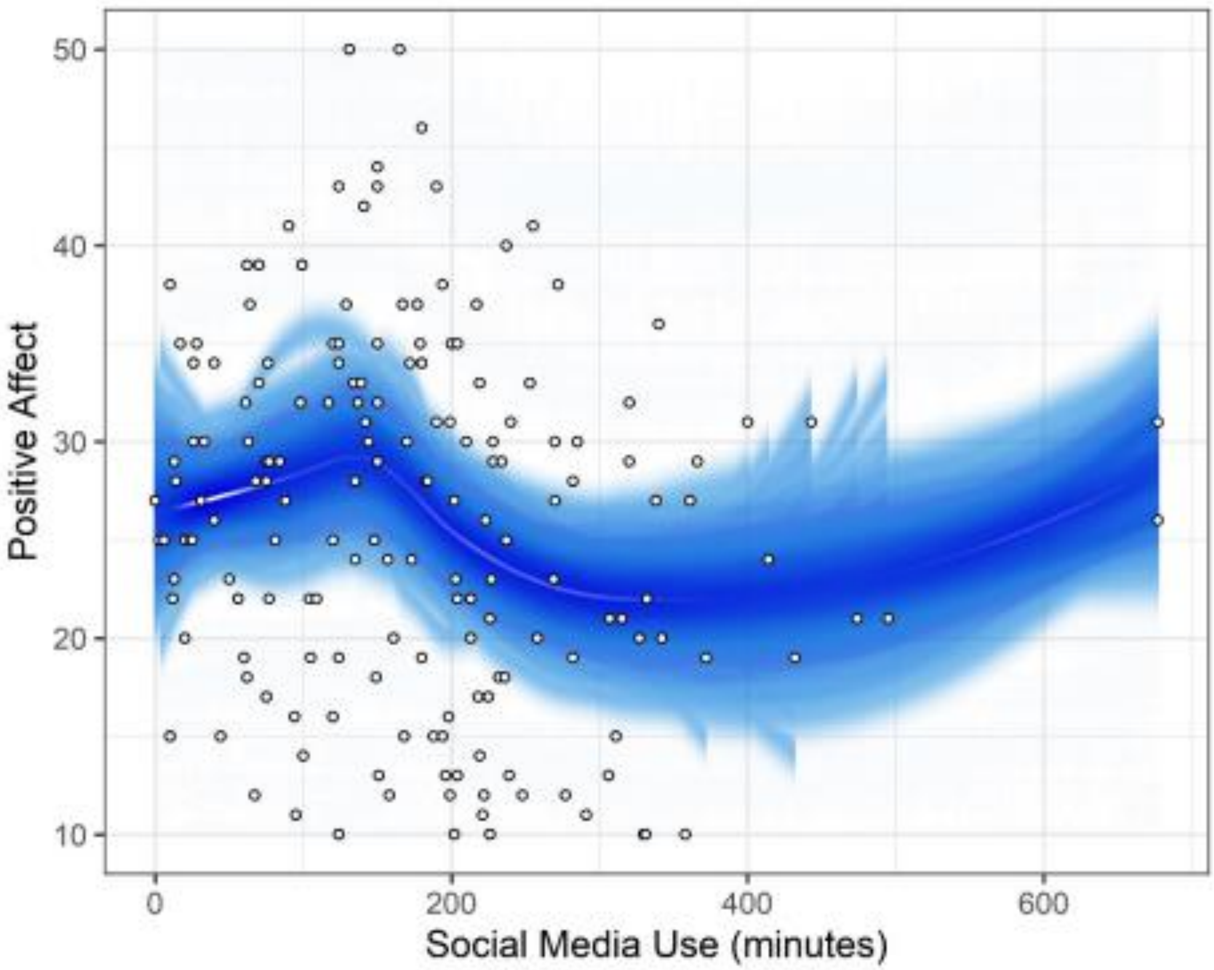


Figure 5

The Relationship between Daily amount of time spent on Social Media applications on an iPhone in minutes, and Positive Affect



Discussion

Overall, this study showed a small, but statistically significant positive relationship between iPhone screen time and negative affect, and social media screen time and negative affect. The results also indicated no statistically significant relationships between iPhone screen time and positive affect, social media screen time and positive affect, nor was there any statistically significant relationships regarding sleep factor variables.

These findings are consistent with the previous literature, in terms of showing a curvilinear pattern (Przybylski & Weinstein, 2017), and a small but statistically significant relationship between screen time and negative affect (Keles, McCrae, & Grealish, 2019), and no relationship for positive affect, similar to Jensen, George, Russell, & Odgers, (2019). While there is a large body of literature assessing self-reported technology use and psychological factors, these have either showed weaker relationships or no relationship at all when actuarial measurements of screen time are involved (see, e.g., Jensen, George, Russell, & Odgers, 2019; Shaw, Ellis, Geyer, Davidson, Ziegler, & Smith, 2020; Sewall, Rosen, & Bear, 2019). While the formal hypothesis test – which assumes a linear relationship between the predictor and outcome was significant in some cases, a visual inspection indicated that this relationship was more complicated, and that screen time may not necessarily lead to psychological harm. Rather, the nonlinear nature of the relationship can show that there may be an undetermined amount of screen time that could actually be healthy and helpful.

The idea that using social media might be beneficial has been expressed in the literature as well. For example, it may lead to greater community and civic engagement (Brusilovskiy, Townley, Snethen, & Salzer, 2016), can be used for developing a sense of community and sharing coping strategies for individuals with serious mental illnesses (Naslund, Aschbrenner, Marsch, & Bartels, 2016)raise awareness, combatting stigma for mental health conditions, provide safe spaces for expression, and coping and empowerment (Berry, Lobban, Belousov, Emsley, Nenadic, and Bucci (2017). Essentially, smartphones and social media could be used in order to help cope with a variety of psychological disorders, and engage with social connections when used in a healthy manner. The present study indicated that for some individuals, their smartphone and social media use may be excessive to the point of being related to reductions in one's mood over time. However, despite their methodological limitations, the literature regarding negative impacts on well-being of technology use still should not be ignored, and should be taken into consideration in these findings. For example, the findings of Eijnden, Lemmens, & Valkenburg (2016) noting social media use being correlated with depression, attention deficits; Primak et al (2017) finding that number of social media accounts being significantly related to symptoms of depression and anxiety; and Shensa et al (2017) noting that internet use patterns mirroring addictive behaviors being predictive of depressive symptoms. When considering the use of these technologies impacting, multivariate factors need to be considered in order to determine in which ways the use can be helpful, and in what ways the use could be harmful. It is possible that social media technologies provide psychological benefits as well as costs. In this case, the benefits could be increased interpersonal interactions and facilitation of socialization, at the potential cost of reducing in-person interactions.

Limitations

In order to be contextually sensitive, it should be noted that the current sample was conducted during the spring semester of 2021 at Murray State University, during the ongoing COVID-19 pandemic crisis. In this timeframe, it is possible and likely that due to current social distancing protocols and measures taken as safety precautions during the pandemic, this sample may have spent more time using smartphones and social media applications than in other circumstances. While this cannot presently be confirmed with comparison for this sample to a previous sample at Murray State University, a replication of this could find different reports of screen time than this current sample. The rationale for this is that since social distancing guidelines, rules, laws, and ordinances may have limited in-person socialization and face-to-face social interactions, participants may have been using their smart devices as a means for social interactions and maintaining social relationships. In addition, consistent with local and state social distancing protocols, the semester for undergraduate students at the time was mostly conducted through online learning, therefore participants may have spent much more time in front of screens than during other periods of time in their lives.

Another limitation is that the people who were included in the analysis are college students, who may not represent the larger population of smartphone users. In addition, these data were reported by the participants themselves, and tracked with participants knowing what data they were reporting. It is possible that participants may have falsely reported their screen time and social media screen time statistics in the survey, possibly for social desirability purposes. One manner in which this could be addressed in a replication would be requesting participants upload screenshots of the screen time statistics page in order to add a layer of validity to responses. Since the study asked participants to look through their smartphone and find their screen time data before reporting it in the survey, there could be an effect of individuals becoming more aware of their usage data, which could influence how much they use their devices as well. Based on reported screen time across study days, participants showed a tendency to maintain their screen time/social media use over the course of their participation in the study. This could indicate that exposure to checking one's daily smartphone use statistics could lead to a maintenance of iPhone use habits. This was a relatively small sample of 97 participants. The timeframe in which data were collected was logistically constrained, and the sample size was smaller than ideal. However, this can be ameliorated by the quality of the dataset, having multiple days of data collection per participant. This is a large amount of insight into a select group of people, but still has limited generalizability to others.

In addition, many of the stressors of participating in a college semester, the COVID-19 pandemic, may have been related to the overall affect of the sample. In previous literature, daily stress has been shown to be related to daily negative affect (Mroczek & Almeida, 2004). There is evidence to suggest that the COVID-19 pandemic had a variety of stress-related outcomes, with the stress resulting from the pandemic and related factors (i.e. knowing friends or family infected with the virus, history of stressful situations and medication problems, and young people who had to work outside of the home) being comparable to traumatic stress during the lockdowns in Italy during early 2020 (Mazza, Ricci, Biondi, Colasanti, Ferracuti, Napoli, & Roma, 2020). One of the findings from Mazza et. al. (2020) relevant to the present study involves increased stress from young adults who worked outside the domicile, which may be a common characteristic of the current sample of Murray State University undergraduates, who often work jobs outside of the residences. In addition, research from the US Department of Health and Human Services/Centers for Disease Control and Prevention indicated large increases in the prevalence of anxiety disorder symptoms (about three times higher than 2019), depressive disorder symptoms (about four times higher than 2019), and that serious consideration of suicide in the past month had doubled in June of 2020 compared to data collected from 2018 (Czeisler, et. al., 2020). An important particular piece of context from this article applied to the present study was that, amongst 18-24 year-olds, serious consideration for suicide in June of 2020 increased to 25.5% (Czeisler, et. al., 2020). Given all of these current features of context in the literature regarding the COVID-19 pandemic, it can be inferred that individuals in this current sample of emerging adults in the COVID-19 pandemic may be using their smart devices longer and more frequently than before, as well as experiencing more significant stressors, symptoms of mental disorders, decreases in mood, and increases in suicide consideration.

As noted previously, the relationships between the predictor variables and negative affect were statistically significant, but may not be interpreted as very strong relationships. This potentially could be explained by some multivariate outliers. For example, one datapoint reported that the individual spent over 16 hours in a single day on their smartphone. While this is technically possible, it is not likely to occur, as that was over 250 minutes more reported time spent than any other individual timepoint in the dataset. Outliers were not removed the dataset, as the outlier responses were plausible (e.g., spending sixteen hours using a device during a single day) . In addition, a small number of participants completed more than seven days of observations. Since this was an unexpected participant behavior and we therefore had no a-priori plan to deal with these cases, these individuals were included in the analyses. However, as a result, participants who completed extra days of the study may disproportionately impact the analytic results more than others in the dataset.

Finally, determining strength in this relationship depends on what one considers to be a marginal increase in negative affect. While an increase of one single minute of daily iPhone screen time may be predictive of a 0.016 point increase on the negative affect scale score (in which the range of scores are between a minimum of 10 and a maximum of 50), if this were to be extrapolated out to multiple hours in a day, the predictive increases in negative affect would likely be considerable (i.e. 100 minutes in iPhone screen time leading to a 1.6 increase in negative affect scaled scores, with a 0.008 error estimate.) However, this is an interpretation of the relationship when forcing the data to fit into a linear model, which may not be the most accurate method of analyzing the relationship.

One part of the results that cannot be determined from the analysis output, but can be seen in the visualizations, is that a linear relationship may be insufficient at describing the nature of the relationship between technology use and psychological characteristics. Specifically, figures 1-4 all showed a nonlinear pattern. This could mean that these relationships are not binary or linear, but can be more complicated than previously assumed. Smartphone use and social media use could potentially involve improvements of mood in some individuals, or provide the opposite effect with others. This is consistent with the previous findings of Przybylski & Weinstein (2017), which the authors titled the "Goldilocks Hypothesis." In this study, a representative sample of over 120,000 English adolescents, the authors noted that the relationships between digital-screen time and mental well-being were nonlinear, indicating that a moderate amount of engagement in digital devices was not actively harmful, while more extreme levels of engagement with digital devices were associated with decreased wellbeing.

Future directions

In continuing the discussion regarding the context in which this sample was collected, future research could aim to replicate this design and findings outside of a pandemic context. This could allow for controlling for the possibility of increased screen time that may have occurred from social distancing measures, and potentially a decrease in overall screen time and social media use when social distancing measures are no longer in place. In addition, a student sample in this context would no longer be in the exclusively online education semesters, may also show a reduction in screen time as more in-person, face-to-face interactions occur in educational settings as well. In a future project replicating this methodology in a similar environment, a comparison could be made for the screen time and social media use were any different in early 2021 compared to other time periods. In addition, more comparisons could be made for sample characteristic differences, such as potential differences in negative affect that may have occurred in the pandemic crisis, such as the high amounts of reported distress during this time period (Czeisler, et. al., 2020; Mazza, Ricci, Biondi, Colasanti, Ferracuti, Napoli, & Roma, 2020).

Some of the previous literature on this topic showed a similar curvilinear pattern as the present results (Przybylski & Weinstein, 2017), indicating that although statistical analyses can be made to try to fit these relationships into a linear model, a linear relationship is not the best way to explain these results. There are a number of potential factors that may be involved in the individuals who display a variety of use patterns that were not addressed in the present study, but should be addressed in future research. First, the present study only looked at affect and sleep characteristics as potential outcomes of screen time and social media use. However, these are merely indicative of how mood could fluctuate with regards to personal technology use, and does not discuss other psychological factors that may be involved. While these relationships may not have been empirically established yet, it may be possible that other psychological factors could serve as moderators or mediators in this relationship. For example, symptoms of some psychopathologies, such as depression or social anxiety, may involve withdrawing socially, and could be related to technology behaviors as a result. Kraut et al. (1998, 2002) did explore this relationship in the earlier days of the internet, noting that greater internet use was longitudinally associated with declines in social circle size, declined family interactions, but these effects did not persist in follow-up studies. Social isolation was not measured in the present study, but could be a possible mediator in this relationship. Although social media predicted negative affect in the present study, that relationship could occur through social isolation where people may rely on these technologies to reduce the feelings of loneliness and reach out to social support. In addition, another external characteristic not accounted for in the present study was perceived social support. This could fit into larger models as potential moderators, wherein individuals who have a high amount of screen time and/or social media screen time, and are high in social isolation could see the effects of social isolation remediate from contacting social supports through high amounts of technology use. In addition, perceived stress should also be accounted for in future research as a factor in the psychological effects of smartphone and technology use broadly. The rationale for including stress in this discussion is that many of these devices are not only used for digital social interactions, but are also used for entertainment purposes. When coping with psychological stressors, individuals may increase their technology usage as a means of reaching out to social support, or as a means of avoidance for aversive stimuli, such as stressors.

One future research direction could explore implications of reductions in screen time as a form of intervention. While there is some existing research suggesting that taking a break from social media platforms may improve well-being (Tromholt, 2016), more research could explore some of the mechanisms of how this may function. For example, Putnam (2000) argues that engaging in a variety of different behaviors has led to a decrease in civil engagement, particularly in the United States. Conceptually, this could explain how to use screen time reductions as an intervention for individuals with significantly low mood. One of the primary treatments for depression in cognitive-behavioral therapy that has a tendency to show reductions in symptoms of depression is behavioral activation (Dimidjian, Martell, Herman-Dunn, & Hubley, 2014) in which a clinician directs clients to engage a variety of behaviors in their environment as a means of becoming in touch with reinforcing stimuli in their environment, thus reducing avoidance of aversive stimuli that maintain depressive symptoms. In this context, reductions of screen time involved with replacement of other, meaningful behaviors and activities could lead to improvements in mood (Dimidjian, Martell, Herman-Dunn, & Hubley, 2014), as the time that would have been spent engaging in a digital device could be replaced. However, the nature of screen time and psychopathology should be explored in research and caution should be exercised before clinicians attempt to use screen time reductions alone as an intervention, as Vally & D'souza (2019) noted that abstaining entirely from social media was actually indicative of negative effects on mood and stress when compared to individuals who used their devices and platforms as usual.

However, in order to determine how clinicians and public health officials could utilize technology behaviors as a potential means of intervention for broad forms of psychological distress, there must be much more research conducted into all of the other potential factors involved that were not measured in the present study. Many variables could be related to positive and negative affect, such as psychodiagnostics, symptoms of psychological disorders like mood disturbances or anxiety, suicidality, life stressors, degrees of perceived as well as actual social support, social isolation, and clinical information. For example, while some individuals in the current study reported relatively high negative affect and relatively high amounts of screen time compared to the rest of the sample, we do not know all the details of their life while data were being collected. One direction future research can take in this regard would be utilizing not only data from individual social media accounts and smartphone use statistics, but also sensitive clinical data, liken to clinical measures used for diagnostic purposes. In addition, the current study does not know what exactly the participants are doing on their smartphones other than how much time they spend using them. In order to tease out the complexity and nature of this nonlinear relationship seen in the current study's results, this topic could benefit from qualitative research on the content that people are posting and/or engaging in, as well as more sensitive data regarding individual clinical psychopathology. Other future qualitative inquiry could be used to determine what other activities people are engaging with on their smartphones. For example, some research could aim to study how much college students spend time using school-related applications, compared to social media, music or video streaming platforms, or gaming applications

There are multiple recent examples of researchers utilizing novel methods, statistical techniques, sensitive clinical datasets, and online behaviors to better understand relationships with psychological factors and technology. For example, Berry, Lobban, Belousov, Emsley, Nenadic, and Bucci (2017) used publicly available information on Twitter to read why people tweeted and created posts about mental health. Qualitative designs similar to this thematic analysis should also be used in future research on this topic, not only utilizing data that is already made available on the internet by users, but also the meaning of content as well. In terms of utilizing this science in a psychosocial intervention, Zirikly, Resnik, Uzuner, & Hollingshead (2019) used data from internet forum-based website, Reddit to focus on suicidality. Specifically, the authors focused on the anonymous, online community of r/SuicideWatch, and utilized pre existing tools of suicide risk assessment, natural language processing, and algorithmic machine learning in order to determine levels of risk for online users based on the language in their posts (Zirikly, Resnik, Uzuner, & Hollingshead 2019). Similar designs have been conducted using other platforms and more sensitive datasets. For example, attempts to develop language-based algorithmic techniques to assess for mental health conditions and suicidality are in development, using confidential data from donated social media account content and data regarding individual suicide attempts (MacAvaney, Mittu, Coppersmith, Leintz, & Resnik, 2021). Although these techniques are still in their infancy, future research should aim to use available information to see how individuals behave online, compared to what they may report confidentially on standardized metrics as well as their offline behaviors, and how this could be used for interventions based on the content that individuals post. These directions of research could help qualitatively breakdown the individual factors involved in the nuances of this relationship, whilst the quantitative inferences can be used to generalize the findings to larger groups.

Appendix A

The Positive and Negative Affect Schedule (Short Form) – PANAS-SF (Watson, Clark, & Tellegen, 1988) :

Indicate the extent you have felt this way over the past day	Very slightly or not at all	A little	Moderately	Quite a bit	Extremely
1. Interested	1	2	3	4	5
2. Distressed	1	2	3	4	5
3. Excited	1	2	3	4	5
4. Upset	1	2	3	4	5
5. Strong	1	2	3	4	5
6. Guilty	1	2	3	4	5
7. Scared	1	2	3	4	5
8. Hostile	1	2	3	4	5
9. Enthusiastic	1	2	3	4	5
10. Proud	1	2	3	4	5
11. Irritable	1	2	3	4	5
12. Alert	1	2	3	4	5
13. Ashamed	1	2	3	4	5
14. Inspired	1	2	3	4	5
15. Nervous	1	2	3	4	5
16. Determined	1	2	3	4	5
17. Attentive	1	2	3	4	5
18. Jittery	1	2	3	4	5
19. Active	1	2	3	4	5
20. Afraid	1	2	3	4	5

Scoring:

Positive Affect Score: Add the scores on items 1, 3, 5, 9, 10, 12, 14, 16, 17, and 19. Scores can Range from 10-50, with higher scores representing higher levels of positive affect

Negative Affect Score: Add the scores on items 2, 4, 6, 7, 8, 11, 13, 15, 18 and 20. Scores can range form10-50, with lower scores representing lower levels of negative affect. The Pittsburgh Sleep Diary (PghSD):

Ratings (place a mark somewhere along the line)

Sleep Quality:

Very bad ……………………………………………………………………… Very good

Mood on final wakening:

Very tense ……………………………………………………………………... Very calm

Alertness on final wakening:

Very sleepy …………………………………………………………………… Very alert

What time did you go to bed last night?

At what time last night did you turn off all your lights and screens?

How many minutes passed (after you turned off your lights and screens) until you fell asleep? Use your best guess.

At what time this morning did you wake up?

Appendix B

MURRAY STATE
UNIVERSITY

Institutional Review Board

328 Wells Hall
Murray, KY 42071-3318
270-809-2916• msu.irb@murraystate.edu

TO:	Sean Rife, Psychology
FROM:	Jonathan Baskin, IRB Coordinator JB
DATE:	2/10/2021
RE:	Human Subjects Protocol I.D. – IRB # 21-107

The IRB has completed its review of your student's Level 1 protocol entitled *Personal Technology Use, Social Media, and Daily Affect in Emerging Adults*. After review and consideration, the IRB has determined that the research, as described in the protocol form, will be conducted in compliance with Murray State University guidelines for the protection of human participants.

The forms and materials that have been approved for use in this research study are attached to the email containing this letter. These are the forms and materials that must be presented to the subjects. Use of any process or forms other than those approved by the IRB will be considered misconduct in research as stated in the MSU IRB Procedures and Guidelines section 20.3.

Your stated data collection period is from 2/10/2021 to 2/9/2022.

If data collection extends beyond this period, please submit an Amendment to an Approved Protocol form detailing the new data collection period and the reason for the change.

This Level 1 approval is valid until 2/9/2022.

If data collection and analysis extends beyond this date, the research project must be reviewed as a continuation project by the IRB prior to the end of the approval period, 2/9/2022. You must reapply for IRB approval by submitting a Project Update and Closure form (available at murraystate.edu/irb). You must allow ample time for IRB processing and decision prior to your expiration date, or your research must stop until such time that IRB approval is received. If the research project is completed by the end of the approval period, then a Project Update and Closure form must be submitted for IRB review so that your protocol may be closed. It is your responsibility to submit the appropriate paperwork in a timely manner.

The protocol is approved. You may begin data collection now.

Opportunity *afforded*

murraystate.edu

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