Smartphone and Social Media use and its Health Associations

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Abstract

While mobile phones offer users communication, information, and entertainment almost instantaneously, there is a growing concern about the impact smartphone and social media use has on mental and physical health. This study addressed gaps in the literature by simultaneously measuring objective and subjective smartphone use rather than relying on subjective reports alone, and then assessed how they were differentially related to health. Generally, it was predicted that measures of smartphone use would be reliable and valid, and that higher use would predict worse health. Overall, a diverse sample (39% White, 22.1% Asian, and 16.9% African American) of 136 young adults (92 female, 44 male) with an average age of 19 (*SE* = .12; Range = 17-25) were assessed twice over a semester on measures of objective and subjective smartphone use and once on aspects of mental and physical health. The results showed that young adults spend approximately four and a half hours a day on their smartphone, with most of that time consumed by social media applications. Their self-report of use was consistent and weakly positively correlated with objective use despite over-estimating use in all categories. After standardizing both measures, there were no differences between objective and subjective smartphone use; however, they were differentially related to health. Generally, subjective measures of smartphone use were better predictors of both mental and physical health. Furthermore, relative time was important for both objective and subjective measures, indicating the relationship between smartphone use and health is not a direct function of time.

Keywords: smartphone; social media; objective; subjective; health; mental health; physical health

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One of the most prominent features in today's technological world is the mobile phone. Currently, the number of active mobile connections exceeds the world's total population (Kemp, 2016). Mobile phones offer users the potential for limitless communication, information, and entertainment at nearly any moment; and, in fact, most individuals now use mobile phones as their primary way to access connected services (Kemp, 2016). However, despite the benefits of greater connectivity, there is a growing concern about how mobile device obsession is affecting health. Moreover, the impact mobile devices have on young adults is particularly important, as they are the first generation to grow up in the age of wireless connectivity. In a 2015 survey, 85% of young adults, aged 18 to 29, reported using a smartphone, with some estimates suggesting that they spend roughly five hours a day on their mobile device (Andrews, Ellis, Shaw, & Piwek, 2015; Smith, 2015). This accounts for almost one third of awake activity when you consider that young adults average close to eight hours of sleep per night (Buboltz Jr et al., 2009). Furthermore, total usage is only expected to grow in the coming years (Kemp, 2016). However, despite the large amount of activity, there appears to be large variability in how people use their smartphone (Falaki et al., 2010). With smartphone use increasing, relatively little is known about the specific ways people use their device as a whole and its impact on health. The current research project explored this issue by first characterizing how a college sample of young adults use their smartphones, and then investigating how that use was associated with mental and physical health.

Social media is just one of the many facets of smartphone use that could take up a large proportion of smartphone activity. In their review, Kaplan and Haenlein (2010) define social media as internet based applications that allow users to produce content in which they can exchange and share. Importantly, social media allows for user-to-user communication and provides a platform for connecting with friends and family while also sharing information. Currently, social media is becoming more popular, with roughly 60% of the North American population using at least one social media platform (Kemp, 2016). Furthermore, social media activity is growing worldwide, with nearly one third of the world's total population using at least one social media account. As expected, Facebook is still the most popular social media platform, reporting around 1.5 billion active accounts as of January 2016, with 83% of users accessing the service on their smartphones (Kemp, 2016). Despite its popularity, however, quantifying social media use on an individual basis has been challenging, with most research evaluating social media use and health utilizing self-report estimates (Bessière, Pressman, Kiesler, & Kraut, 2010; Jelenchick, Eickhoff, & Moreno, 2013; Levenson, Shensa, Sidani, Colditz, & Primack, 2016; Lin et al., 2016). The current study addressed these shortcomings by obtaining a quantitative measure of social media use. Additionally, this study assessed how objective social media use related to subjective use. Finally, as with smartphone use, this study explored how social media use related to mental and physical health.

Mental Health: Depression and Suicide

With smartphone and social media use expected to increase in the coming years, there has been growing concern about how it is affecting mental health (Kemp, 2016; Murphy, 2016). Of particular concern is the relationship between smartphone and social media use and depression. Depression is a critical area of research provided that depression is a strong predictor of suicide even after controlling for relevant socio-demographic factors (Zhang & Li, 2013). Furthermore, suicide is the second leading cause of death for people under 30 years old with an estimated 800,000 people committing suicide each year (World Health Organization, 2016). The

World Health Organization reports that suicide rates are highest in groups that experience discrimination, conflict, disaster, violence, abuse, and a loss or a sense of isolation. There is a growing idea that smartphone activity may be partially to blame as depression scores were found to be higher in people who used their smartphones more often (Demirci, Akgönül, & Akpinar, 2015). Yet, research was not clear as to the reason people were using their smartphones. It is possible that social media use is related to depression and suicide as it potentially provides an environment for some of the before mentioned suicidal predictors to occur (e.g. conflict, abuse, violence). However, the relationship between social media use and depression is still unclear, as studies exploring the issue have found mixed results (Bessière et al., 2010; Jelenchick et al., 2013; Lin et al., 2016). For example, some studies have found no association between symptoms of depression and self-reported Facebook use (Jelenchick et al., 2013); while other studies have suggested that social media use could elicit small decreases in depression (Bessière et al., 2010). Ellison, Steinfield, and Lampe, (2007) suggested that decreases in depression among Facebook users is not surprising and attribute the effect to the large amount of social resources Facebook provides (i.e. social support, bolstering self-esteem, life-satisfaction etc.). Nevertheless, it is important to note that these studies were conducted with limited samples and explored the effects of social media use based solely on estimates from one or two social media platforms. In reality, this may not represent real world social media activity (low external validity) as smartphone users have the ability to access numerous social media platforms on their mobile device for any amount of time. However, some work which evaluated social media use based on multiple platforms found a strong positive association between depression and the amount of time spent on social media (Lin et al., 2016). Although the relationship between social media and depression is still poorly understood, one idea is that social media puts the user at an increased risk for conflict, abuse, and cyber bullying, which could be a path to increased depression and possibly suicidal ideation. The current study contributed to this literature by characterizing smartphone and social media activity with objective and subjective measurements before exploring how those measures related to depressive symptoms.

Mental Health: Perceived Stress

Another mental health component that might be related to smartphone and social media use is perceived stress. Stress is a psychological and physiological mechanism that helps mobilize the body in the presence of a perceived stressor; however, if it persists for a long period of time, stress can be detrimental to health by suppressing immune function (Dhabhar, 2000). Furthermore, past research has demonstrated that stress and depression are related in young adults, with many studies finding higher stress predicted higher depression (Brandy, Penckofer, Solari-Twadell, & Velsor-Friedrich, 2015). However, the relationship between smartphone activity and stress is just as unclear as it is with depression. Much like depression, studies have found that higher levels of smartphone use are associated with higher levels of stress (Wang, Wang, Gaskin, & Wang, 2015); yet, research does not dissociate the reasons people use their smartphones. It is possible that social media may be an important factor. Some researchers suggest that people use social media in response to stress as a way to attain social support (Nabi, Prestin, & So, 2013). Studies have revealed that perceived social support is negatively associated with stress (Brandy et al., 2015; Nabi et al., 2013). That is, the higher a person perceives their support, the lower their perceived stress. Additionally, researchers have found that the more friends people reported having on social media, the higher their perceived social support (Nabi et al., 2013). Although these studies did not look at actual social media use, the results suggest that social media might be beneficial in relation to stress; however, recent empirical evidence suggests this may not be the case (Bevan, Gomez, & Sparks, 2014; Campisi et al., 2012). One of the few studies to evaluate general social media use and stress found that the more time participants reported spending on social media the higher their reported stress (Bevan et al., 2014). Additionally, it was found that the more social media accounts participants had was associated with higher perceived stress. Furthermore, some studies have even found that stress may actually be induced from Facebook use (Campisi et al., 2012). In their study, Campisi and colleagues found that the majority of their respondents indicated that using Facebook was stressful, with those reporting higher levels of stress being more susceptible to developing an upper respiratory infection. Additionally, almost a third of respondents also indicated that unplugging their Facebook connection would reduce stress. Campisi and colleagues suggested that stress was induced by negative interpersonal relationships such as rejecting friend requests and defriending others. However, much like depression, the relationship between smartphone activity, social media use, and stress is still poorly understood. The current study added to this literature by characterizing smartphone and social media activity utilizing both objective and subjective measurements, and then assessed its relationship with stress.

Mental Health: Anxiety

Anxiety is another mental health factor that could relate to smartphone and social media use. Previous research has identified a high comorbidity between stress, depression, and anxiety (Cummings, Caporino, & Kendall, 2014; Dobson, 1985). In fact, one study found that 67% of students who were anxious were also depressed and 61% were also stressed (Mahmoud, Staten, Hall, & Lennie, 2012). Furthermore, it appears that college students are particularly vulnerable with over half of those who visited a student health clinic citing anxiety as a concern (Brown, 2016), with some studies estimating that at any point in time, 15.6% of college students screen positive for an anxiety or depression disorder (Eisenberg, Gollust, Golberstein, & Hefner, 2007). Naturally, this begs the question, what factors contribute to the high rates of anxiety in this population. One factor emerging in research is smartphone and social media use. While research is still limited and methods from study to study vary, there is evidence of an association between heavy smartphone use and higher rates of anxiety (Boumosleh & Jaalouk, 2017; Cheever, Rosen, Carrier, & Chavez, 2014; Elhai, Levine, Dvorak, & Hall, 2016; Enez Darcin et al., 2016; Hwang, Yoo, & Cho, 2012; Lepp, Barkley, & Karpinski, 2014). However, as previously stated, these studies varied in their assessment of smartphone and social media activity. Furthermore, most research measured activity subjectively in an ordinal fashion (i.e. low, medium, high). This may not be the best way to conceptualize smartphone and social media use given the high rates of activity (Kemp, 2016). This study was able to add to this literature by characterizing smartphone and social media activity utilizing both objective and subjective measurements, and then assessed its relationship with anxiety.

Physical Health: Sleep

Along with mental health, research should evaluate smartphone and social media activity and its association with physical health. Specifically, the current study evaluated sleep quality, as proper sleep is important for both the mind and body. Insufficient sleep can lead to decrements in mood, cognition, metabolism, and immune function while also increasing stress and weight (Grandner, Patel, Gehrman, Perlis, & Pack, 2010). Furthermore, lack of sleep leads to overall poor health. College students appear to be at an increased risk for the health decrements associated with the lack of sleep, as 88.5% of students report at least occasional sleep problems (Buboltz Jr, et al., 2009). There are numerous biological, psychosocial, and environmental factors that can contribute to poor sleep; however, until relatively recently almost nothing was known about the specific effects of smartphones (Demirci, Akgönül, & Akpinar, 2015). In their study, Demirci et al. (2015) found that higher amounts of smartphone use were associated with more sleep disturbance. However, this again begs the question as to the specific aspects of smartphone use that relate to sleep disturbance. It is possible that social media activity plays a role. In fact, Levenson et al., (2016) found that sleep disturbance and social media use were related. Specifically, the more time young adults were on social media and the higher the number of overall visits were associated with greater sleep disturbance.

Cain and Gradisar (2010) proposed three possible mechanisms for sleep disturbance and media use. First, it is possible that smartphone or social media activity interfere with sleep by directly displacing it. For example, someone who is on their smartphone or on social media more often at night will have less time to sleep. Second, smartphone or social media use my cause physiological arousal that can prevent or delay sleep. For example, someone may find it difficult to sleep if they are being stimulated by talking or texting with peers or checking social media feeds. Third, blue wavelength light from devices such as a smartphones may affect circadian functioning by suppressing melatonin. Furthermore, Murphy (2016) suggests sleep patterns may be disturbed by smartphone activity. Additionally, sleep deprivation from smartphone use could be caused by the fear of missing phone calls or messages. Although the results of Demirci et al., (2015) and Levenson et al., (2016) suggest that higher smartphone and social media use are associated with more sleep disturbance, these results were based on self-report estimates. The current study added to this literature by characterizing smartphone and social media activity using both objective and subjective measurements, and then explored their associations with sleep quality.

Physical Health: Obesity and Physical activity

Another important component of physical health that may be related to smartphone or social media use is obesity and physical activity. Currently, it is estimated that 1.9 billion adults are overweight, and 600 million are obese (World Health Organization, 2015). Additionally, the obesity epidemic appears to be affecting youth, as The World Health Organization estimates that about 42 million children are now overweight or obese. Obesity is a very serious health concern as it increases the risk for negative health outcomes such as heart disease, stroke, diabetes, musculoskeletal disorders, and even cancer. Furthermore, the rise in obesity is partially due to the decrease in physical activity (Hill, & Peters, 1998).

The rise of obesity and the decline of physical activity are partially attributed to the increase in sedentary lifestyles (Blümel et al., 2015). Some studies have shown that high media use increased the likelihood of obesity (Nelson, Gortmaker, Subramanian, Cheung, & Wechsler, 2007); however, these results were for all media outlets including television and computers. One general thought has been that media use may increase the risk of obesity by displacing the time typically used to exercise. Most research looking at smartphone, social media use, obesity and physical activity do so in the context of behavioral intervention tools (Allen et al., 2013; Li, Barnett, Goodman, Wasserman, & Kemper, 2013), with little research being conducted outside of this context. However, a recent study found that high social media users spend more time sitting even on non-work days (Alley et al., 2016), which as a result could lead to increased weight and less physical activity. The current study added to this literature by characterizing smartphone and social media activity using both objective and self-report measurements, and then explored their associations with measures of obesity and physical activity.

Physical Health: Vision, hearing, thumb, neck, and back pain

In addition to sleep, obesity, and physical activity, there are a number of other physical health symptoms that may be related directly to smartphone or social media use. Some of the most reported symptoms include vision and hearing problems along with thumb, neck, and back pain (Murphy, 2016).

Handheld devices like smartphones require users to operate their device closer to their face, which could result in dry eyes, double vision, fatigue, light sensitivity, or headaches (Murphy, 2016; Vision Council, 2016). The Vision Council (2016) reports that 65% of Americans experience eye strain from digital devices, with young adults under 30 showing the highest rates of strain. However, despite the high prevalence of eye strain, it is unclear what aspect of smartphone use contributes to vision problems. It is possible that smartphone use as a whole increases the rates of eye strain, or specific aspects of smartphone use, such as social media, are to blame for this problem. The current study examined if objective and subjective measures of smartphone and social media use are related to vision problems.

Hearing issues are another problem that could develop from smartphone use. Typically, young adults use earbuds or headphones with personal audio devices like smartphones, and many are exposed to unsafe levels of sound (Murphy, 2016). Studies report that over 15% of young adults are exposed to potentially damaging sound levels from their portable device, and most report symptoms of tinnitus, difficulty focusing, asking someone to repeat themselves, and having to increase television volume (Herrera, De Lacerda, Lurdes, Alcaras, & Ribeiro, 2016; Vogel, Van de Looij-Jansen, Mieloo, Burdorf, & de Waart, 2014). Additionally, 10% of young adults reported some kind of permanent hearing damage due to their listening habits (Vogel et al., 2014). Furthermore, Vogel and colleagues found that experiencing these decrements in hearing was associated with more symptoms of depression and thoughts of suicide. The current study added to this literature by evaluating if symptoms of hearing impairment were related to quantitative or self-report measures of smartphone and social media use.

Another important aspect of physical health and smartphone use is pain. Typically, smartphones are small enough to fit in the palm of the user's hand. Users often position their device in ways that can cause thumb, neck, or even back pain in order to see adequately (Kim, 2015; Murphy, 2016; Vision Council, 2016). Repeated gripping, typing, and gaming on a hand-held device can require a wide range of unnatural motions for the thumb, which can ultimately cause damage to the tendon. Furthermore, by positioning the device to see adequately, smartphone users may bend forward or look down more frequently. This can cause increased weight on the spine, which could cause it to become inflamed or damaged. Furthermore, pain has been shown to be associated with an increase in depressive symptoms (Calvo-Lobo et al., 2017). The current study evaluated thumb, neck and back pain and its relationship with objective and subjective measures of smartphone and social media use.

Physical Health: Inflammation

The final physical health factor the current study investigated was inflammation. Inflammation is the body's response to invading microbes, in which white blood cells accumulate to eradicate pathogens (Miller, & Blackwell, 2006). This inflammatory response is directed by inflammatory cytokines (i.e. interleukin-6, IL-6) which act as signaling molecules to direct cells to the infection. Furthermore, inflammation has been linked to several psychological and physiological conditions such as chronic stress, depression, chronic pain and heart disease (Howren, Lamkin, & Suls, 2009; Miller, & Blackwell, 2006; Segerstrom, & Miller, 2004; Zhang, & An, 2007). However, much like the other components of health discussed previously, there is little understanding of how inflammation relates to smartphone use, or technology use for that matter. However, in their meta-analysis, Howren et al. (2009) found the elevated levels of the inflammatory markers c-reactive protein (CRP) and IL-6 were associated with more symptoms of depression. Additionally, increased levels of CRP and IL-6 are also found in people experiencing chronic stress (Miller & Blackwell, 2006). Furthermore, symptoms of depression and stress have been found to be positively associated with smartphone and social media use (Bevan et al., 2014; Campisi et al., 2012; Lin et al., 2016). Therefore, it is possible that increased levels of smartphone or social media use are associated with higher levels of inflammatory markers. The current study added to the literature on inflammation by assessing its relationship with smartphone and social media use.

Smartphone use vs. Social media use

With most young adults accessing social media on their smartphones (Kemp, 2016), a natural question to ask is whether it is smartphone use, social media use, or both that are related to poor health (higher depression, higher stress, higher anxiety, poor sleep quality, higher obesity, lower physical activity, higher physical symptoms, and higher inflammation). Although the topic of social media has gained interest in research, in most instances, social media use is evaluated separate of smartphone use, has only accounted for one or two social media platforms, and has typically been assessed with self-report measures (Bessière et al., 2010; Jelenchick et al., 2013; Levenson et al., 2016; Lin et al., 2016). The current study addressed these shortcomings by obtaining both objective and subjective measures of smartphone and social media use, which, allowed for a more accurate illustration of how young adults used their smartphone, and specifically, how often they used it for social media. Additionally, by measuring smartphone and social media use subjectively, this study achieved insight into just how accurate people’s perceptions of their smartphone and social media use are. Furthermore, by obtaining objective usage from smartphones, the current study was able to accurately evaluate if smartphone use and social media use differentially affected health.

Objective vs Subjective use

Most research investigating the relationships between smartphone and social media use and health obtained self-report estimates of activity. While self-report measures are often more convenient to acquire, consideration is rarely given to the validity of these measures when assessing them with health outcomes. Furthermore, a concrete understanding on the differences between perception and behavior is needed to make more general conclusion about smartphone use and health. While cognitive literature on time-perception suggests individuals are poor at estimating durations (Grondin, 2010), only a handful of studies have evaluated this in the context of smartphone activity. Still, despite limited investigation, research suggests individuals over-estimate their smartphone activity (Boase & Ling, 2013; Junco, 2013; Scharkow, 2016). Furthermore, overestimations were valid as a strong positive relationship was found between reported and actual Facebook, Twitter, and email use (Junco, 2013). However, with large individual variation in how young adults use there smartphones (Falaki et al., 2010), a more holistic evaluation is need. This study added to the literature and evaluated the relationship between objective and subjective total smartphone use as well as the different categories of use to achieve a more comprehensive understanding of time-perception and smartphone activity. Furthermore, this study also evaluated how the two types of use differentially affected health.

Aims and hypotheses

The current study had three main aims. The first aim was to characterize how a college sample of young adults use their smartphone, and in particular, how often they use social media applications on their smartphone. This was done by obtaining objective data from the participant's smartphone, in addition to obtaining self-reported use. It was predicted that young adults would spend most of their time on social media, and both objective and subjective use would be stable over-time. The second aim was to evaluate if young adults' perceptions of their smartphone activity were accurate in regard to their actual usage. It was hypothesized that the subjective measures would demonstrate validity and reliability.

The third aim was to investigate the association between smartphone and social media use with health (Figure 1). Specifically, it was hypothesized that objective and subjective measures of smartphone and social media use would be related to poor mental health (e.g., more symptoms of depression, stress, and anxiety) and poor physical health (e.g., more sleep disturbance, higher obesity, less physical activity, more problems associated with vision, hearing, and thumb, neck, and back pain, and higher inflammation).

Method

Participants

Participants (*N* = 136) were recruited as part of a larger study investigating smartphone and social media use and its relationship with psychological, physiological, and performance outcome variables (see Table 1 for descriptive characteristics). Participants were recruited in one of two ways. First, participants were recruited through the psychology subject pool (SONA), where students earned course credit for their research participation. Second, participants were recruited through fliers posted on campus, and were compensated $30 for completing all parts of the study. A participant was considered eligible for this study if they were an Apple or Android smartphone user, between 17-25 years old, and were able to speak, read, and write in English.

Additionally, participants were considered ineligible for participation if they were: currently using tobacco products, taking medication for anxiety or depression, using a heart pacemakers or automatic defibrillator, had tinnitus or were deaf, had head trauma with a loss of consciousness 6 months prior to the study, had an injury two weeks prior to the study, had seizures or neurological disease, had cancer, had a history of significant coronary events (e.g. ischemia, heart attack, bypass surgery, etc.), had high blood pressure or cholesterol, had diabetes or a history of hepatitis c, had a chronic infection such as HIV or an active infection such as a cold or flu, had severe anemia, had a diagnosis of connective tissue disease (e.g. arthritis, systemic lupus erythematosus, scleroderma, Sjogren's syndrome, polymyositis, dermatomyositis, and vasculitis), had an illness not controlled by a therapeutic regimen, were taking anabolic steroids or epinephrine medications (for example, rescue inhaler, Epi-Pen, decongestant, etc.), were taking anti-inflammatory medicines such as pain pills (e.g. aspirin, ibuprofen, Advil, Aleve, Celebrex, etc.), taking opioid medications (e.g. hydrocodone, oxycodone, morphine, methadone, etc.), underwent surgery, chemotherapy, or radiation therapy within two weeks prior to the study, or gave birth 6 weeks prior to the study.

Measures

The current study measured smartphone and social media use, depressive symptoms, stress, anxiety sleep quality, obesity, physical activity, and physical symptoms, which included vision and hearing problems, along with thumb, neck, and back pain.

Smartphone and Social media use

The current study evaluated how often young adults use their smartphones and how often they use social media. Additionally, this study sought to evaluate the accuracy of a self-report smartphone and social media use scale with its objective counterpart. Thus, the current study measured both objective and subjective smartphone and social media use.

Self-report. The current study used a modified Ellison Facebook Intensity Scale to measure young adult's reported smartphone and social media use (Ellison et al., 2007). The Facebook intensity scale is a measure of self-reported Facebook activity and the extent to which Facebook is part of an individual's daily routine. Furthermore, the Facebook Intensity Scale displayed adequate internal consistency (Cronbach's $\alpha = .83$). The current study modified the Facebook Intensity Scale to include other popular social media platforms and commonly used smartphone applications as well as other potential disconnected activities (see *Appendix* for complete scale). The scale asked participants to estimate how much time they spend on each application or activity. Participants were given the choices "0 – I do not use this application", "1 – Less than 30 minutes", "2 – 30-60 minutes", "3 – 1-2 hours", "4 – 2-3 hours", "5 – 3-4 hours", "6 – 4-5 hours", and "7 – more than 5 hours". The scale was scored in the same way as Steinfield, Ellison, and Lampe (2008) in which the selections were recoded to reflect the midpoint of time in minutes for each category. For example, if a participant selected "3- 1-2 hours", then this was recoded as 90 minutes. Next a measure of subjective total smartphone use was created by summing all the items for which participants could use their smartphone. Additionally, the scale was able to be broken down into specific categories of subjective use (i.e. social media, texting, calling, etc.). Furthermore, by scoring the Facebook Intensity Scale this way, researchers were able to evaluate the proportion of time in any given category of smartphone use. For example, if a participant estimated that they spent a total of 10 hours on their smartphone per day, and they also reported that 2 of those hours were spent on social media applications, then 20% (.2) of their reported smartphone activity was spent on social media.

Objective use. The way objective smartphone and social media use were measured depended on the type of smartphone participants reported having.

iPhone. Participants with an Apple iPhone used the built-in battery function of the Apple operating system. This function allowed users to see how much time in hours and minutes they spent on individual applications during the past seven days. Furthermore, it allowed the researcher to calculate average use per day by dividing this total use by seven.

Android. Participants with Android smartphones were asked to download the free application ‘PhoneUsage’ from the play store. The ‘PhoneUsage’ application monitors the number of hours, minutes, and seconds participants spent on individual smartphone applications. The ‘PhoneUsage’ application records usage continually from the time it is downloaded. However, to be consistent with the iPhone, the study only evaluated usage over roughly a seven-day period, and calculated average use per day.

Regardless of the type of phone, both objective measures were free to use and ran in the background while participants used their smartphones. Furthermore, both methods only recorded the amount of time participants had the applications open on their screen and did not collect any information about their specific activity in the application. Importantly, both objective measures allowed for the same characterization of use. First, a total amount of time spent on the smartphone was calculated by summing the number of hours and minutes participants spent on each individual application. This summation provided the total time participants spent on their smartphones during roughly a one-week period. In the event that participants had more or less than seven days of usage, all objective smartphone data were divided by the number of days of data collection to get an estimate of use per day, which was subsequently used for all analyses.

Furthermore, these measures allowed the researcher to investigate for what young adults were using their smartphones. Specifically, the activities participants used their smartphones for were separated into eight different categories. These categories were social media, texting, calling, internet browsing, work or educational purposes, gaming, health promotion, and other. The way participant's smartphone activity fell into each category was calculated two different ways. First, the total time participants used their smartphones for each respective category was calculated by summing all applications that fell into that category. For example, the total amount of time participants spent on social media was calculated by adding the time spent on each individual social media application (e.g. Facebook, Twitter, Snapchat, Instagram etc.). The second way these categories were evaluated was by creating a proportion of use relative to total smartphone activity. This was accomplished by taking the total amount of time participants spent in a specific category and dividing it by the total amount of time participants spent on their smartphones. For example, if a participant spent a total of 30 hours on their smartphone, and 12 of those hours were spent on social media applications, then 40% (.4) of their total smartphone activity was spent on social media.

Depression

Depressive symptoms were measured using the Center for Epidemiologic Studies Depression Scale-Revised (CESD-R; Eaton, Smith, Ybarra, Muntaner, & Tien, 2004). The CESD-R is a 20-item questionnaire that closely reflects the DSM criteria for depression and is a frequently used tool for screening depression and depressive disorder. The scale has five response options ranging from "not all or less than 1 day", "1-2 days", "3-4 days", "5-7 days", and "nearly every day for 2 weeks". Furthermore, the CESD-R has shown great internal consistency (Cronbach's $\alpha = 0.93$; Van Dam & Earleywine, 2011).

Stress

Stress was measured on the Perceived Stress Scale (PSS; Cohen, Kamarck, & Mermelstein, 1983). The PSS is a 10 item self-report scale that measures the degree to which situations in one's life are appraised as stressful. Responses on the scale range from "0-Never" to "4-Very often". Cohen, Kamarck, & Mermelstein (1983) reported Cronbach's α between .84-.86 for the PSS, and test-retest reliability as .85.

Anxiety

Anxiety was measured using the State-Trait Anxiety Inventory (STAI; Spielberger et al. 1983). The STAI has 40 items, 20 items that assess state anxiety (e.g. "I am tense" and "I feel nervous") and 20 items that assess trait anxiety (e.g. "I feel like a failure" and "I feel inadequate"). The STAI measured state and trait anxiety on a likert scale from "1 - Almost Never" to "4 - Almost Always", with higher scores indicating higher anxiety.

Sleep quality

Sleep quality was measured using the Pittsburgh Sleep Quality Index (PSQI), which was a 19 item self-report questionnaire that assessed sleep quality over a 1-month time interval (Buysse, Reynolds, Monk, Berman, & Kupfer, 1989). The PSQI had good internal consistency (Cronbach's α = 0.83)

Obesity

Obesity was measured using two different methods. First, the study calculated the participant's body mass index (BMI), which was the measure of body fat based on weight in kilograms divided by height in meters squared. Participants self-reported their height and weight in the demographics section and this was used to calculate BMI. The second way obesity was measured was using the waist-to-hip ratio method. The waist-to-hip ratio was calculated by measuring the waist circumference halfway between the lowest rib and the iliac crest, and hip circumference by measuring the widest point over the buttocks (Dalton et al., 2003).

Physical activity

Physical activity was measured using the Godin Leisure-Time Activity Questionnaire, which asked participants to estimate the amount and intensity of their physical activity over a typical week (Godin, & Shephard, 1997). The current study used the total leisure activity score to get a measure of physical activity. Godin and Shephard (1985) reported a total reliability coefficient of .74 for the questionnaire.

Physical Symptoms

Physical Symptoms including vision and hearing problems, and thumb neck and back pain were measured using the Cohen-Hoberman Inventory of Physical Symptoms (CHIPS) (Cohen & Hoberman, 1983). The CHIPS scale measured the perception of burden from physical symptoms and the resulting psychological effects. Participants rated from “0-that they have not been bothered by the problem” to “4- the problem has been an extreme bother.” A total score of physical symptoms was created by summing across all items. Furthermore, a subscale of the items for vision and hearing problems, and thumb neck and back pain was created. The CHIPS scale had good internal consistency (Cronbach's $\alpha = 0.88$). The current study modified the original scale from 33 questions to 38 questions to include physical symptoms that would be specific to mobile phone use (e.g. hearing and vision problems etc.).

Inflammation

Inflammation was measured using blood samples. For this study, an 8mL sample of blood was collected by venipuncture into an 8mL serum separator tube. After allowing time for coagulation, the samples were centrifuged to collect serum and then temporarily frozen. The inflammatory markers interleukin-6 (IL-6) and c-reactive protein (CRP) were then measured in the serum using enzyme-linked immunosorbent assay (ELISA) technique preformed in duplicate.

Procedure

The current study was divided into two parts.

Phase 1

The first phase of the study was conducted online. Participants who volunteered for the study were directed to a Qualtrics survey to complete Phase 1. Once in Qualtrics, participants were provided a detailed description of the study and completed an online informed consent document that outlines the procedures for both Phase 1 and Phase 2 of the study. Additionally, participants verified their eligibility and then answered demographic questions. Next, participants completed the modified Ellison Facebook Intensity Scale. Finally, participants were asked to either take a screenshot of their battery usage if they were an iPhone user, or download the ‘PhoneUsage’ application if they were an Android user.

Phase 2

Participants who completed phase one were contacted through email with instructions and a link for participating in Phase 2. In the email, participants were asked to schedule an appointment to come in to the lab and complete Phase 2. All appointments occurred at least seven days after a participant completed Phase 1 to allow for sufficient time to collect objective smartphone data for Android users. Once participants came to the lab for Phase 2, a phlebotomist collected an 8 mL sample of blood, and a researcher obtained a measure of their waist and hip circumference so that the waist-to-hip ratio could be calculated. After the measurements, participants were asked to provide their smartphone and social media use data. Participants then used a computer to complete questionnaires evaluating subjective smartphone use, quality, physical activity, and physical symptoms. Next, participants completed a brief (10-15minute) attention and memory task, which was used for another study. After the cognitive tasks, participants completed questionnaires measuring depressive symptoms, stress, and anxiety. Once finished, participants were thanked and compensated accordingly.

Results

Data Screening

Phase 1

In Phase 1, 65 people provided objective data. Of those 65 people, only 55 had valid data usable for analysis. Specifically, 10 cases were discarded due to missing information (i.e., missing information about the number of days data had been collected) or lack of visibility. Additionally, we measured subjective smartphone use at Phase 1 for the 136 participants who completed Phase 2. However, examination of subjective smartphone use revealed one case with missing data on subjective game and health use. That case was excluded from analyses, leaving 135 valid cases for subjective use.

An examination of the skewness values, box plots, and histograms was conducted for all Phase 1 objective and subjective smartphone use measures that were used for analysis. This examination revealed that total objective use, objective social media use, objective other use, subjective internet use, and subjective other use were all normally distributed in their raw form. However, objective texting, objective calling, subjective texting, subjective call, subjective work or educational use, and subjective game use were all slightly positively skewed. Consequently, square root transformations were performed on these variables to make them normally distributed. Finally, objective internet use, objective work or educational use, and subjective social media use were all severely positively skewed. As a result, log transformations were performed on these variables to make their distributions normal.

Phase 2

Before testing the aims and hypotheses, all Phase 2 variables were screened for missing values. Overall, data were collected from 136 participants; however, some participants had missing data on some measures. The number of missing cases by measure are as follows: unreported race (n = 4), unreported income (n = 5), missing objective smartphone use (all categories and proportion) (n = 6), WHR not obtained (n = 3), missing sleep quality (n = 8), missing physical activity (n = 4), missing blood sample (n = 17), unreliable blood serum assay results (n = 10). The measures of gender, difficulty paying bills, subjective smartphone use (all categories and proportion), perceived stress, depressive symptoms, physical symptoms, neck pain, back pain, thumb pain, hearing problems, and vision problems had complete data for all participants. Participants with missing data on a measure were excluded on relevant analyses.

Examination of the skewness values, box plots, and histograms was conducted for all Phase 2 measures. The examination revealed that objective smartphone use, objective social media proportion, objective texting proportion, subjective smartphone use, subjective social media use and proportion, subjective texting use, subjective calling use and proportion, subjective internet browsing and proportion, subjective game proportion, perceived stress, sleep quality, and WHR were all normally distributed in their raw form. However, objective social media use, objective internet use, subjective work and educational use, depressive symptoms, physical symptoms, and physical activity were all slightly positively skewed. Consequently, a square root transformation was conducted on these variables to make their distributions normal. Additionally, objective texting, objective calling and proportion, objective internet proportion, objective work and education use and proportion, objective game use and proportion, objective other use and proportion, subjective texting proportion, subjective work or education proportion, subjective game use, back pain, neck pain, vision problems, hearing problems, Il-6, and CRP were all highly positively skewed. Thus, log transformations were performed on these variables to make them more normal.

The examination also revealed that the amount of time between participating in Phase 1 and Phase 2 varied for participants; specifically, while at least one week had to pass between Phase 1 and Phase 2, the time between participating ranged from one to approximately 14 weeks, with a median of approximately two weeks. As a result, the number of days between Phases was controlled in correlation analyses assessing the relationship between use over-time. Additionally, the examination revealed variables that could not be included in analyses due to a lack of variation. Explicitly, relationship status and thumb pain showed over 95% of the sample not married or living with a partner and not bothered by pain, respectively. Consequently, these variables could not be analyzed. Additionally, all objective and subjective use of health applications at both Phase 1 and Phase 2 had at least 77% of the sample with no use at all. Thus, only nonparametric statistics could be used to evaluate health-related smartphone use.

Data Analysis

The current study had three main aims. The first aim was to characterize, both objectively and subjectively, how a college sample of young adults use their smartphone, and in particular, how often they use social media. Additionally, this study explored use in the categories of texting, calling, internet browsing, work or educational use, gaming, health use, and other. It was predicted that young adults would spend most of their time on social media, and that smartphone use would be stable over-time. First, descriptive statistics were used to characterize use, and the proportions for all categories were created (see *Method* for a detailed description). Next, partial correlations controlling for the number of days between Phase 1 and Phase 2 and controlling for self-reported change in smartphone and application activity were used to assess the relationship between use over-time, and Wilcoxon sign rank tests were used to evaluate mean differences in smartphone use over-time. It was hypothesized that smartphone use would be stable and neither objective nor subjective measures of use would change. Additionally, an independent *t*-test (Mann-Whitney U for health applications) was conducted to ensure that the participants who had objective data at Phase 1 (n = 55) did not use their smartphones any differently at Phase 2 than the participants who did not have data at Phase 1 (n = 75). It was hypothesized that those who provided screenshots at Phase 1 were not an artifact of sampling error, and were no different from the rest of the sample. Finally, *t*-test's and ANOVA's were used to assess demographic differences in smartphone use based on gender, race, income, and relationship status.

The second aim was to evaluate if young adults' perceptions of their smartphone activity were accurate. That is, were self-report measures of smartphone use reliable in relation to actual use. Specifically, it was hypothesized that self-report measures would demonstrate reliability and validity. Spearman's rho correlations were used to assess the relationship between objective use and subjective use at both Phases of the study. Next, differences in objective and subjective measures were tested using dependent *t*-tests. Before conducting the dependent t-tests, both measures were standardized using z-scores. Finally, to determine if the relationship between measures of objective and subjective use differed over-time, the correlations between objective and subjective use at Phase 1 were compared to the respective correlations at Phase 2. Specifically, the dependent correlations were compared using Silver, Hittner, and May's (2006) Depcor.exe Fortran program. The tests performed included Williams's *t*, Dunn and Clark's *z*, and Steiger's modification using average *r* and average *z*.

The third aim was to investigate the association between smartphone and social media use and health. Specifically, it was hypothesized that objective and subjective measures of smartphone and social media use were related to poor mental health (e.g., more symptoms of depression, stress, and anxiety) and poor physical health (e.g., more sleep disturbance, higher obesity, less physical activity, more problems associated with vision, hearing, and thumb, neck, and back pain, and higher inflammation). In addition to social media, this study explored the association between other aspects of smartphone use (e.g. texting, calling, internet browsing, work or education use, and gaming) and health. Hierarchical linear regression models were used to test all hypotheses. Since this study was exploratory, no correction was made for multiple comparisons. Before exploring how smartphone use related to health, t-test and ANOVAs were used to verify gender, financial burden, and age as theoretically important covariates, and were subsequently used when predicting all health outcomes. Additionally, physical activity is an important variable to consider when evaluating obesity (WHR and BMI) and inflammation (IL-6 and CRP), and was added as an additional covariate for those outcomes. Furthermore, obesity was a theoretically important variable to consider when evaluating inflammation, thus, BMI was added to analyses predicating inflammation. For all regression models except total smartphone use, the covariates were entered on step one, the total time and the proportion of time in a given category (i.e. social media, texting, calling etc.) were entered on step two, and the interaction term between total time and the proportion of time was entered on step three. The slopes, beta weights, and partial and semi-partial correlation coefficients were used to determine the importance of each predictor in the regression model. It was predicted that worse health would be associated with both a higher total time and a higher percentage of use. Furthermore, significant interactions were probed using the Johnson-Neyman procedure in Process (Hayes, 2018) as it allowed us to identify the point(s) along a continuous moderator where the relationship between the predictor and the outcome became statistically significant.

Aim 1

The first aim of the project was to characterize, both objectively and subjectively, how a college sample of young adults use their smartphones, and how often they use social media. Additionally, this study explored use in the categories of texting, calling, internet use, work or educational use, gaming, health use, and other. Another goal of Aim one was to determine if measures of smartphone use were stable over-time. Specifically, it was predicted that young adults would spend most of their time on social media, and smartphone use would not change over-time.

Objective Use

Objective use from the iPhone battery function and the Android 'PhoneUsage' application was first converted into average use per day (see *Method*). The average objective time in minutes, standard error, 50^{th} percentile, minimum, maximum, and proportion of total smartphone use for all objective categories were listed in Table 2. As predicted, social media was the highest category of smartphone use followed by texting and internet use. Next test-retest reliability for objective smartphone use was explored in the 55 individuals who provided valid data at Phase 1. First, the partial correlations were analyzed between Phase 1 and Phase 2 objective use while controlling for the number of days between Phase 1 and Phase 2 and the self-reported change in habits (Table 3). All correlations showed a significant positive association with a moderate to strong relationship. Next, a Wilcoxon sign rank test was conducted to determine if objective use differed from Phase 1 to Phase 2. No significant differences were revealed for objective measures of smartphone use regardless of type (Table 4). These findings supported the hypothesis that objective smartphone use would show test-retest reliability.

In order to make more accurate generalizations about objective smartphone use over-time, an independent *t*-test (Mann-Whitney U for health applications) was conducted to ensure that those who provided a screenshot at Phase 1 did not use their smartphones any differently. Specifically, we wanted to make sure there were no differences in Phase 2 objective data between the 55 people who provided a screenshot at Phase 1 and the other 75 people who did not. Generally, no differences were found between people who did and did not have objective data at Phase 1; however, those who provided objective data at Phase 1 called for more minutes per day (M = 20.47, SE = 2.76) than those without objective Phase 1 data (M = 11.07, SE = 2.58), $t(128) = -4.51$ $p < .001$, $d = .81$.

Subjective Use

Subjective use from the modified Facebook Intensity Scale was converted in to estimated minutes of use per day (see *Method*). The average subjective time in minutes, standard error, 50th percentile, minimum, maximum, and proportion of total smartphone use for all subjective categories are listed in Table 5. Again, as predicted subjective social media was the highest category of smartphone use, followed by work or educational use and texting. Next, test-retest reliability for subjective use was explored. First, the partial correlations were analyzed between Phase 1 and Phase 2 subjective use while controlling the number of days between participation and the change in habits (Table 6). All correlations between subjective use at Phase 1 were significant and positively correlated with the subjective use at Phase 2, and, except for internet browsing, all correlations were moderate to strong while controlling for self-reported change. Next, a Wilcoxon sign rank test was conducted to determine if subjective use differed from Phase 1 to Phase 2. No significant differences were revealed for subjective measures of smartphone use regardless of type (Table 4). These findings supported the hypothesis that there was test-retest reliability in subjective use over-time.

Next, demographic differences in objective and subjective smartphone use were explored. Specifically, an independent samples *t*-test and a one-way ANOVA were utilized to assess differences in objective and subjective smartphone use based on gender, race, and income. A significant difference was found in objective game use by gender, $t(62.0) = 4.14$ $p < .001$, $d = .82$. Males ($M = 15.83$, $SE = 3.47$) spent more time per day playing games on their smartphones than did females ($M = 4.88$, $SE = 1.22$). Additionally, there was a difference in subjective game use based on gender $t(89.7) = 2.83$ $p = .006$, $d = .38$. Males reported more time gaming ($M = 70.23$, $SE = 16.36$) on their smartphones than did females ($M = 43.53$, $SE = 8.05$). For both *t*-tests there was a violation in Levene's test for equality of variance, thus, these analyses were interpreted with equal variances not assumed. Other than game use, there were no significant differences in objective or subjective total smartphone use, social media use, texting, calling, internet browsing, work or educational use, health, or other types of use based on gender. Additionally, no significant differences were found based on race or income for all types of objective and subjective use (i.e., total smartphone use, social media, texting, calling, etc.).

Aim 2

The second aim of the study was to evaluate if young adults were accurate in their perceptions of their smartphone use. Namely, was self-reported use valid. First, we tested if there were difference in objective and subjective measures for any category of use at any phase. This was accomplished by first standardizing both measures using z-scores and then running dependent *t*-test's. The results revealed no differences between objective and subjective measures of smartphone use for any category (i.e. social media, text, calling, internet use etc.). Next, Spearman's rho correlations were used to further examine the relationship between objective use and subjective use at Phase 1 and Phase 2 (Table 7). Specifically, all categories at both Phases, with the exception of internet browsing and work or educational use, had moderate to strong positive correlation between objective and subjective use. Game use had the strongest association at both phases. As expected, emerging adults perceived their use with some level of accuracy. However, most relationships were moderate, indicating some level of distortion between perceived and actual smartphone use.

Another goal of Aim 2 was to determine if the magnitude of the relationship between objective and subjective use remained stable or varied over-time. While controlling for the number of days between participation and self-reported change in habits, it was found that there were no differences between Phase 1 and Phase 2 in the strength of the relationships between objective use and subjective use for any of the indices (Williams's *t*, Dunn and Clark's *z*, and Steiger's modification using average *r* and average *z)*. These findings provided support for the reliability of the strength of the relationship between objective and subjective use.

Aim 3

The third aim of the study was to evaluate how smartphone and social media use related to health. Specifically, it was hypothesized that objective and subjective measures of smartphone and social media use would be related to poor mental health (e.g., more symptoms of depression, stress, and anxiety) and poor physical health (e.g., more sleep disturbance, higher obesity, less physical activity, more problems associated with vision, hearing, and thumb, neck, and back pain, and higher inflammation). Importantly, this study evaluated if the total amount of time, the proportion of time, or the interaction between the two related to worse health. It was predicted that a higher total use and a higher proportion of use would be related to worse health outcomes.

Hierarchical linear regression models were used to examine how objective and subjective measures of smartphone use and different aspects of smartphone use (e.g. social media, texting, calling, internet browsing, work or educational use, and gaming) related to health. Specifically, this study evaluated depressive symptoms, stress, anxiety (state and trait), sleep quality (sleep latency and sleep duration), obesity (WHR and BMI), physical symptoms (vision problems, hearing problems, neck pain, and back pain), and inflammation (Il-6 and CRP) as health outcomes. See Figure 1 for a conceptual model for which all analyses (except total smartphone use) follow. In total there were 17 health outcomes that were explored, significant findings were discussed below.

Objective Use

Total Smartphone Use. Higher smartphone use predicted higher physical activity while controlling for the covariates (Table 8.). However, total objective smartphone use did no predict the other outcomes.

Social Media Use. Objective social media use predicted physical activity and IL-6 inflammation (Table 9). Specifically, more time on social media every day predicted higher physical activity and IL-6 inflammation over and above the covariates. Additionally, a higher proportion of social media use predicted lower physical activity, and the interaction between total time and the proportion of time that was social media predicted physical activity over and above the individual predictors alone. Figure 2 showed the Johnson-Neyman values in which the x-axis depicted the centered moderator (proportion of social media use) and the y-axis depicted the continuous range of values for the adjusted effect of objective social media use on physical activity. Specifically, at a proportion of social media use of .4735 and below (55.56% of the sample), the adjusted effect of objective social media use on physical activity became significant and more positive as the proportion of social media use decreased.

Texting. Objective texting predicted depressive symptoms, physical activity, and BMI (Table 10). Specifically, a higher proportion of texting predicted lower BMI. While total objective texting and the proportion of texting did not predict any other health outcomes, the interaction between them predicted depressive symptoms and physical activity. Figure 3 showed the Johnson-Neyman values in which the x-axis depicted the centered moderator (proportion of Texting) and the y-axis depicted the values for the adjusted effect of objective texting per day on depressive symptoms. Specifically, at a proportion of texting of .1624 and above (24.62% of the sample), the adjusted effect of texting on depressive symptoms became significant and more positive as the proportion increased. Additionally, Figure 4 showed the Johnson-Neyman values for the adjusted effect of texting on physical activity. At a proportion of texting of .0283 and above (78.57% of the sample), the adjusted effect of texting on physical activity became significant and more positive as the proportion increased.

Calling. Objective calling only predicted IL-6 inflammation (Table 11). While the total objective time and the proportion of time spent calling did not individually predict IL-6 inflammation, their interaction did. Figure 5 showed the Johnson-Neyman values in which the x-axis depicted the centered moderator (proportion of calling) and the y-axis depicted the values for the adjusted effect of objective calling per day on IL-6. At a proportion of calling of .0032 and above (66.67% of the sample), the adjusted effect of calling on IL-6 inflammation became significant and more positive as the proportion increased.

Internet Browsing. Objective internet browsing predicted IL-6 inflammation (Table 12). Specifically, higher total time per day spent internet browsing predicted higher IL-6 inflammation, and a higher proportion of time predicted lower inflammation. However, while total time and proportion of time were unique predictors, they only marginally accounted for variance over and above the covariates in the regression model.

Work or Educational Use. While the total objective time and the proportion of time spent on work or educational applications did not uniquely predict depressive symptoms, their interaction did (Table 13). Figure 6 showed the Johnson-Neyman values in which the x-axis depicted the centered moderator (proportion of work or education) and the y-axis depicted the values for the adjusted effect of objective work or education use on depressive symptoms. Specifically, at a proportion of work or educational use of .1481 and above (6.15% of the sample), the adjusted effect on depressive symptoms became significant and more positive as the proportion of use increased.

Gaming. A higher proportion of use that was gaming predicted lower levels of IL-6 inflammation (Table 14). However, objective gaming use did not predict the other outcomes.

Subjective Use

Total Smartphone Use. Higher subjective smartphone use predicted higher IL-6 inflammation (Table 15). However, total smartphone use was not a predictor of the remaining outcomes.

Social Media Use. Subjective social media use predicted trait anxiety, physical activity, neck pain, and IL-6 inflammation (Table 16). Specifically, higher total subjective time spent on social media predicted higher physical activity and IL-6 inflammation over and above the covariates. Additionally, a higher proportion of social media use predicted higher trait anxiety and neck pain, and lower physical activity.

Texting. Subjective texting was found to predict depressive symptoms, IL-6, and CRP inflammation (Table 17). Specifically, higher total subjective time spent texting predicted higher IL-6 and CRP inflammation. Additionally, a higher proportion of time texting predicted lower depressive symptoms and IL-6 inflammation. While subjective texting and the proportion of texting accounted for variances over the covariates for IL-6 inflammation, the overall model change was only marginal for depressive symptoms and CRP inflammation.

Calling. Subjective calling predicted depressive symptoms, WHR, and IL-6 inflammation (Table 18). Higher subjective time calling predicted higher depressive symptoms and IL-6 inflammation. Additionally, a higher proportion of time that was calling significantly predicted lower WHR and IL-6. While total subjective calling and the proportion were unique predictors of depressive symptoms, the overall model change after accounting for the covariates was only marginal.

Internet Browsing. Subjective internet browsing predicted depressive symptoms, physical symptoms, vision problems, and IL-6 and CRP inflammation (Table 19). Specifically, more internet browsing was a predictor of higher IL-6 inflammation. Additionally, a higher proportion of internet browsing predicted lower depressive symptoms, physical symptoms, IL-6, and CRP inflammation. While the proportion of subjective internet browsing was a significant predictor of depressive symptoms, physical symptoms, and CRP inflammation, it only marginally accounted for variance above the covariates in these regression models. Furthermore, the interaction between internet use and the proportion of use significantly predicted vision problems. Figure 7 showed the Johnson-Neyman values in which the x-axis depicted the centered moderator (proportion of subjective internet use) and the y-axis depicted the values for the adjusted effect of subjective internet use per day on vision problems. Specifically, at a proportion of internet use of .1109 and above (26.47% of the sample), the adjusted effect of internet use on vision problems became significant and more positive as the proportion of internet use increased.

Work or Educational Use. Subjective work or educational use on the smartphone predicted physical symptoms, physical activity, and neck pain (Table 20). Specifically, higher total work or educational use on the smartphone predicted higher physical activity. Additionally, a higher proportion of work or educational use was a predictor of lower physical symptoms, physical activity, neck pain, and IL-6 inflammation. However, although the proportion uniquely predicted physical symptoms, neck pain, and IL-6 inflammation in the overall model, the only marginally accounted for model variance over the covariates.

Gaming. Higher subjective game use predicted higher stress, depressive symptoms, physical symptoms, WHR, BMI, and CRP inflammation (Table 21). While subjective game use predicted BMI and CRP in the overall model, it only marginally accounted for model variance above the covariates.

Discussion

With smartphone and social media activity on the rise (Kemp, 2016), this study addressed many gaps in the existing literature by distinguishing smartphone use with objective and subjective methods before exploring their associations with health. Specifically, this was one of the first studies to evaluate total smartphone use, and different categories of use, while simultaneously applying objective and subjective methods. By assessing use in this fashion, this study uniquely characterized total smartphone activity and discerned the differences between the two types of measures. Furthermore, this study then used these characterizations to predict mental and physical health, and overall found that different aspects of smartphone use predicted worse health. Unexpectedly, objective and subjective measures of smartphone use differentially predicted health. Generally, subjective smartphone measures were found to be better predictors of both mental and physical health. Additionally, for both measures of use, the proportion of time relative to total use and the interaction terms were important and uniquely predicted some aspects of health. However, the interaction terms proved particularly important for objective smartphone use as five of the six interactions were found with objective data. Although these findings demonstrated the initial reliability and validity of the scales, future studies should further examine their psychometric properties so that more specific conclusions about smartphone use and health can be made.

Reliability and Validity of Smartphone Use

Generally as expected, Aim 1 and Aim 2 suggested that both objective and subjective measures were reliable and valid. The results from Aim 1 showed that objectively, college students spend approximately four hours and thirty minutes on their smartphone every day, which corroborated past research that estimated young adults spend five hours each day on their mobile device (Andrews et al., 2015; Smith, 2015). As expected, social media activity was the highest category of smartphone use, and accounted for a little under two hours of that time. A similar pattern was observed with subjective measures of activity as social media use was again the highest reported category of use. Next, this study assessed if smartphone and social media use remained stable over-time, and as expected, this was supported. Specifically, both objective and subjective measures of smartphone use did not differ from Phase 1 to Phase 2, and all relationships between measures were significantly related over-time with a moderate effect. This suggested that while there was some variation in smartphone use over-time, the overall patterns of use remained relatively consistent. This would be expected as day-to-day activities, responsibilities, and obstacles influence use slightly. Additionally, with the exception of males gaming longer than females, no demographic differences were found in how young adults used their smartphones.

Next the study assessed if subjective measures of smartphone use were valid, and found that this was partially supported. Similar to past findings (Boase & Ling, 2013; Junco, 2013; Scharkow, 2016), this study found that college students over-estimated their smartphone activity for all categories of use. While the current study did not ask participants to estimate their overall smartphone use directly, it was inferred by adding the amount of time reported for any smartphone category or application. Consequently, young adults reported more smartphone use then was physically possible in a 24 hour period, which suggested they might not consider the big picture (overall use) when estimating different aspects of use. However, despite young adults over-reporting their use, there were no differences between objective and subjective measures of smartphone activity when both scales were standardized. Furthermore, the correlations indicated young adults were relatively accurate in predicting all aspects of their smartphone activity with the exception of internet browsing and work or educational use. Similar to the conclusions drawn by Junco (2013), there were a couple of interpretations for why college students might be inaccurate in these areas. First, it was possible that when self-reporting use, college students were including internet browsing and work or educational use on devices other than their smartphone. Consequently, this use would not have been captured by objective measures, thus resulting in poor accuracy for those categories. Alternatively, the inaccuracy for those categories may, to some extent, reflect demand characteristics. In an attempt to be a model student, participants may have overestimated their work and school related activities. One final interpretation may be that college students were poor at estimating the amount of time they spend on tasks they do not find enjoyable (work or school). In addition to accuracy, the study also revealed that the magnitude of the relationship between objective and subjective smartphone use was not different at Phase 1 and Phase 2, indicating that the relationships between the two were reliable. With evidence of reliability and validity for objective and subjective smartphone measures, the study then explored the specific associations these measures had with mental and physical health.

Mental health

In recent years there has been a growing concern about how smartphone and social media use is impacting our mental health (Kemp, 2016; Murphy, 2016). The final Aim of the study explored this concern and assessed how objective and subjective measures of overall smartphone use and different aspects of use (e.g. social media, texting, calling, internet browsing, work or educational use, and gaming) related to mental health. Specifically, it was hypothesized that higher use would be related to poorer mental health (e.g. more symptoms of depression, stress, and anxiety). The results indicated this hypothesis was only partially supported as many analyses did not show an association.

Despite the measures showing no difference when standardized, it was found that overall subjective smartphone use was a better predictor of mental health. Specifically, only the interaction effects for objective texting and objective work or education use predicted depressive symptoms; at lower proportions of social media use and higher proportions of texting, a stronger positive relationship between objective time and depressive symptoms was revealed. While overall the effects were weak according to Cohen's (1988) standards, these findings were not surprising based on the evidence in past literature. Specifically, it has been suggested that some employees use their smartphones to be connected to work at all hours which might subsequently increase stress, reduce relaxation during non-work hours, and lead to more symptoms of depression and burnout (Pitichat, 2013). Furthermore, past research has also identified an association between more frequent texting and higher depression (Skierkowski & Wood, 2012).

In contrast to objective measures, subjective measures proved a much better predictor of mental health as aspects of subjective use predicted depression, stress, and anxiety. Specifically, higher subjective time calling and gaming predicted higher depression. Additionally, higher proportion of social media use predicted higher trait anxiety, and a higher proportion of texting and internet browsing predicted lower depression. However, despite subjective use being a better predictor of mental health, all observed effects were considered weak. Furthermore, while the positive relationships between reported game use and depression and stress was not surprising in the context of past literature (Baranowski, Buday, Thompson, & Baranowski, 2008; Desai, Krishnan-Sarin, Cavallo, & Potenza, 2010), the finding that reported calling predicted higher depression was curious. Given the negative relationship between social support and depression (Ellison, Steinfield, & Lampe, 2007), this finding would suggest that those who reported higher calling did not perceive calling as support but as an intrusion or stressor that negatively impacted their health (Thomée, Eklöf, Gustafsson, Nilsson, & Hagberg, 2007). Furthermore, the fact that higher calling predicted higher depression for subjective measures but not for objective measures highlighted the importance of perception, and future research should evaluate how changing perception impacts health. Additionally, as expected, this study found evidence of a positive association between the proportion of social media use and anxiety which aligned with past research (Boumosleh & Jaalouk, 2017; Cheever et al., 2014; Elhai et al., 2016; Enez Darcin et al., 2016; Hwang et al.,2012; Lepp, et al., 2014). However, unexpectedly, no association was found with social media use and depression and stress which did not support past research suggesting a positive relationship (Bevan et al., 2014; Campisi et al., 2012; Jelenchick et al., 2013; Lin et al., 2016; Wang et al., 2015). A logical future step would be to separately examine social media use and mental health for the different social media platforms.

Despite some predictions about smartphone and social media use and mental health not being supported, some interesting patterns emerged in significant models. First, the associations between smartphone use and mental health were overall weak (Cohen, 1988), with use predicting between three to six percent of the variance in mental health outcomes. Second, total smartphone use did not predict mental health for either objective or subjective use which suggested it was not the amount of time an individual spends on their smartphone that related to mental health, but moreover, what individuals did with their smartphones. Third, the relative amount of time (i.e. proportion of use) and the interaction between total time and the relative time uniquely predicted mental health. This suggested that the relationships between aspects of smartphone use and mental health were not as simple as the amount of time a person spends using their phone. Fourth, subjective smartphone use was a better predictor of mental health overall, which suggested that perceptions of use might be important predictors for components of health that have subjective components (i.e., mental health). Future research should keep these findings in mind and attempt to experimentally manipulate perceptions of use to get a better understanding of how it related to mental health.

Physical Health

In addition to mental health, this study also explored how objective and subjective measures of overall smartphone use and different aspects of use related to physical health. It was hypothesized that higher use would be related to poorer physical health (e.g., more sleep disturbance, higher obesity, less physical activity, more problems associated with vision, hearing, and thumb, neck, and back pain, and higher inflammation). Again, this hypothesis was only partially supported as many analyses did not show an association.

Although, objective and subjective smartphone use both predicted physical health, subjective use was a better predictor overall as it predicted more physical health outcomes. Furthermore, with the exception of objective work or education use, all categories of objective and subjective use showed a relationship with some aspect of physical health. Unexpectedly, smartphone use did not show any associations with sleep quality; however, objective and subjective measures showed relationships with obesity, physical activity, physical symptoms, and inflammation.

Obesity and Physical Activity. Specifically, it was found that a higher proportion of objective texting predicted lower BMI, and higher subjective game use predicted a higher BMI and WHR, with all effects considered weak. While it was not surprising that game use was positively related to obesity (Nelson, Gortmaker, Subramanian, Cheung, & Wechsler, 2007), the negative relationship between objective texting and obesity was not expected. It is not initially clear why higher texting would be related to lower obesity; however, one explanation might be indirectly explained from the results found with physical activity. Specifically, it was found that higher objective total smartphone use and higher social media use related to higher physical activity with a weak effect, and a higher proportion of social media use related to lower physical activity with a medium effect. In addition, the interactions revealed the effect of social media use on physical activity was significant and positive only if individuals had a low proportion of use, while the effect of texting on physical activity was significant and positive for those with a high proportion. Given the portability of smartphones as well as the progression of applications and wearable technology available to help individuals achieve fitness and health related goals (Patel & O'Kane, 2015), it is not surprising that individuals who exercised more also may have used their smartphones more. Moreover, with a portable multi-media device in the palm of their hand, it would have been relatively convenient and easy for individuals to catch up on social media or hold text conversations while exercising. The caveat was that at higher proportions of social media use the relationship did not exist. While Patel and O'Kane (2015) found that individuals use their smartphones in the gym for a variety of reasons (i.e. distraction, disruption, information etc.), future research would be needed to investigate the specific ways young adults use their smartphones while exercising, and how those different reasons related to physical activity.

Physical Symptoms and Pain. Interestingly, objective categories of smartphone use did not predict physical symptoms, but many different subjective categories did. Specifically, higher subjective game use predicted more overall physical symptoms with a weak effect. This finding supported past research that found a positive association between gaming and pain (Wei, Chen, Huang, Bai, 2012). Additionally with a weak effect, this study found that a higher proportion of subjective internet and work or education use predicted fewer physical symptoms. While it is not explicitly clear why this might have been, one interpretation might be that those who used their phone more for internet browsing or work and education use were engaging with their phone less during these activities (i.e. less scrolling, swiping, or typing and more reading) which might result in few overall symptoms. By exploring the individual symptoms this study was able to find evidence of this idea. Specifically, the interaction for vision problems showed that as the proportion of subjective internet use increased, the positive effect of subjective internet use on vision problems became stronger. This finding would be expected if someone spent more time reading on a small mobile device (Vision Council, 2016). However, future investigations should delineate the differences between type of use, and how those differentially related to physical symptoms. In addition to the individual symptom of vision problems, higher neck pain was predicted from a higher proportion of social media use with a weak effect. While this supported prior research suggesting heavy smartphone users have more pain due to a non-neutral neck position (Kim 2015), future investigations are needed as it is was not clear why only a higher proportion of subjective social media use related to more neck pain.

Inflammation. The hypothesis that higher smartphone and social media use would relate to higher inflammation was partially supported. Specifically, even while controlling for theoretically important covariates like obesity and physical activity, it was found that more objective time on social media and internet browsing predicted higher IL-6 inflammation. In addition to the total objective time, a higher objective proportion of internet browsing and game use predicted lower IL-6 inflammation, and the interaction for calling showed that as the proportion of calling increased, the positive effect of calling on IL-6 inflammation became stronger. In addition to objective use, subjective smartphone use also predicted IL-6 inflammation. Specifically, higher subjective smartphone use, social media use, texting, calling, and internet browsing predicted higher IL-6 inflammation. Furthermore, the proportion of subjective use that was texting, calling, internet browsing and work or education use predicted lower IL-6 inflammation. While the hypothesis that total smartphone and social media use would relate to higher inflammation was generally as expected, all effects were considered weak by

Cohen's (1988) guidelines. However, the rationale for many of the observed findings are unclear. Specifically research has found that inflammation related positively to a number of negative health outcomes such as depression, anxiety, chronic pain, and heart disease (Howren et al., 2009; Lin et al., 2016; Miller & Blackwell, 2006), and initially, it was hypothesized that inflammation would relate to smartphone and social media use indirectly through some of the expected negative outcomes of use (i.e. depression and stress)However, this idea was not supported as smartphone and social media use did not relate to many of the expected negative health outcomes for either measure of activity. Future research is necessary to understand the mechanisms through which smartphone use, as well as different aspects of use, related to inflammation. While both objective and subjective measures of use predicted IL-6 inflammation, only subjective smartphone use predicted CRP inflammation. Specifically, more subjective time spent texting and gaming predicted higher CRP inflammation, while the proportion of subjective internet use predicted lower CRP inflammation all with a weak effect. Again, it was important to note that these analyses were exploratory, and the explanation for the observed relationships were unclear. Despite the fact that the relationships between smartphone use and inflammation were poorly understood, it is important to consider that BMI was a very large predictor of both inflammation measures. By controlling for such a large predictor, it became easier to predict the remaining variance. Ultimately, future research is necessary to fully understand the observed relationships between smartphone use and inflammation.

Despite some predictions about smartphone and social media use and physical health not being supported, some interesting general patterns emerged in those models that were significant. First, the associations between smartphone use and physical health were overall stronger than those observed with mental health, with use predicting between 2 - 13 percent of the variance in physical health outcomes. According to Cohen (1998), these were small-to-medium effects with most associations being a small. Second, while objective measures of use were better predictors for physical health then mental health, subjective measures were able to predict more physical health outcomes. This suggested that in addition to mental health, subjective measures of use were also better indicators of physical health. Third, only subjective measures predicted physical symptoms, and like mental health, this suggested that subjective estimates are important for physical health measures with a subjective component, such as pain and discomfort. Fourth, the relative amount of time and the interaction terms not only predicted mental health, but also aspects of physical health as well. Overall this suggested that the relationship between smartphone use and health is more complex than the amount of time an individual uses their phone.

Limitations

As with all research, there were limitations in the present study. First, despite young adults spending a large proportion of their awake activity on their smartphones, this study did not record social media or other application use that was not on their smartphone. Second, although they are two of the most popular brands (Mohd, 2013), this study was strictly limited to Apple and Android smartphone users. Furthermore, obtaining observed smartphone data was dependent on participants capturing iPhone data at Phase 1 for collection later at Phase 2. Additionally, the iPhone reference period at Phase 1 and Phase 2 was sometimes not 7 days as requested. Similarly, observed smartphone data for Android users was dependent on participants installing a tracking application, which made it impossible to assess smartphone use at Phase 1. However, this limitation was expected, and the current study converted all data to represent use per-day which helped combat this issue. Furthermore, future research could address these shortcomings by developing a monitoring application that is universal across all devices. A third limitation is that the time between participants completing Phase 1 and participating in Phase 2 was not consistent for all individuals. While at least one week had to pass between Phase 1 and Phase 2, the time ranged from one to approximately 14 weeks, with a median of approximately two weeks. Ultimately, this limitation was also anticipated, and thus we controlled for the amount of time that passed between Phase 1 and Phase 2 in test-retest reliability assessments. However, future research should attempt to standardize the time between assessments as the change in smartphone use over-time is still poorly understood. Fourth, to some extent, participants were aware that their smartphone habits were being monitored, and this awareness may have biased reported use. Researchers expected, and controlled for this by having participants report subjective change in activity due to the monitoring, which was then controlled for in appropriate analyses. However, if participants chose not to report their change in habits or changed their use unconsciously, this bias was not accounted for in analyses. A final limitation was that this study was correlational and causality could not be drawn. While longitudinal data on smartphone and social media use allowed us to establish reliability of the predictor variables, this study was purposely designed in an exploratory fashion as many of the relationships with health were either poorly established or not established at all. However, future investigations should try to manipulate smartphone and social media use to explore causal pathways.

Conclusion

This study was one of the first to evaluate total smartphone use and different categories of use while also applying objective and subjective methods. By using this approach, we uniquely characterized objective and subjective smartphone activity as a whole and showed that young adults spend most of their time on social media. Although, subjective measures overestimated the objective data, the distortion was consistent and, after standardizing the values, there were no difference between the two types of measures. Further examination of concurrent objective and subjective use suggested that subjective measures are relatively accurate and provided validity for the numerous research studies implementing self-report estimates. While exploratory in nature, this study generally suggested objective and subjective use differentially predicted health. Although objective measures provided a more accurate picture of smartphone use in the young adult population, subjective measures were better predictors of both mental and physical health outcomes. This implied that researchers need to consider how an individual's perception may be related to health outcomes with subjective components (e.g. mental health and pain). Furthermore, the results of this study suggested that the relative amount of time and the interaction provided important information when predicting health. Collectively, the findings of this study illustrated just how complex the relationship between health and smartphone use is. Namely, improving health may be more complex than a simple reduction of use.

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Tables

Table 1. Demographics and frequencies

	Frequency	Percent	Mean	SE
Age	136	100.0%	19.16	0.12
Gender	136	100.0%	-	-
Male	44	32.4%	-	-
Female	92	67.6%	-	-
Race	136	100.0%	-	-
White	53	39.0%	-	-
African American	23	16.9%	-	-
American Indian	3	2.2%	-	-
Asian	30	22.1%	-	-
Pacific Islander	2	1.5%	-	-
Other	21	15.4%	-	-
Missing	4	2.9%	-	-
Type of Smartphone	136	100.0%	-	-
iPhone	95	69.9%	-	-
Android	41	30.1%	-	-

Table 2. Objective smartphone use descriptives

Category of Use	Average	SE	Median	Minimum	Maximum	Proportion
Phase 1 (N = 55)						
Social Media	119.99	8	120.86	0	297.14	.4187
Texting	32.8	3.77	24	0	138	.1126
Calling	22.39	2.92	16.71	0	84	.0783
Internet	21.39	3.02	13.67	0	115.72	.0828
Work or Educational	9.75	3.33	3.14	0	169.86	.0367
Gaming	10.46	2.77	0	0	72.86	.0352
Health	0.1472	0.08	0	0	3.71	.0006
Other	65.34	4.65	55.6	18.71	136.57	.2351
Total Smartphone use	282.27	11.9	268.29	97.57	514.67	1.0000
Phase 2 (N = 130)						
Social Media	115.46	5.56	111.64	0	323.71	.4380
Texting	27.78	2.31	19.44	0	153	.1056
Calling	14.97	1.93	6.29	0	150.86	.0534
Internet	20.79	1.62	15.84	0	92.57	.0849
Work or Educational	8.66	1.17	4.99	0	86	.0388
Gaming	8.25	1.42	0	0	84	.0317
Health	0.38	0.19	0	0	21	.0016
Other	65.09	4.56	56.57	3.75	293.6	.2460
Total Smartphone use	261.39	8.86	257.09	10.9	598.2	1.0000

Note. The proportion of use is = [category use] / total smartphone use. All values, except the proportion, represent number of minutes of use per day

Table 3.

Correlation between objective use at phase 1 & phase 2

Type of Use	**N**	**Pearson product**	***p***
Social Media	54	0.582	.000
Texting	54	0.703	.000
Calling	54	0.443	.001
Internet Browsing	54	0.644	.000
Work & Educational	54	0.579	.000
Gaming	54	0.822	.000
Health	54	0.715	.000
Other	54	0.647	.000
Total Smartphone	54	0.495	.000

Note. All correlations evaluated while controlling for self-reported change in app use and smartphone use as well as the number of days between Phase 1 and Phase 2

Table 4. Wilcoxon signed rank test. Testing differences in objective and subjective phase 1 and phase 2 smartphone data

	Type of Use	**N**	***Z***	***p***
Objective Use				
	Social Media	54	-.031	.975
	Texting	54	-.286	.775
	Calling	54	-.186	.853
	Internet Browsing	54	-.733	.463
	Work & Educational	54	-.523	.601
	Gaming	54	-.838	.402
	Health	54	-.943	.345
	Other	54	-.952	.341
	Total Smartphone	54	-.232	.816
	Type of Use	**N**	***Z***	***p***
Subjective Use				
	Social Media	135	-.083	.934
	Texting	135	-1.269	.204
	Calling	135	-2.200	.028
	Internet Browsing	135	-.633	.526
	Work & Educational	135	-1.748	.080
	Gaming	135	-1.593	.111
	Health	135	-.825	.409
	Other	135	-.641	.521
	Total Smartphone	135	-.652	.514

Table 5. Subjective smartphone use descriptives

Category of Use	Average	SE	Median	Minimum	Maximum	Proportion
Phase 1 (N = 135)						
Social Media	537.33	28.27	480	45	1710	.3640
Texting	155.67	10.6	150	0	600	.1033
Calling	83.11	7.73	45	0	330	.0518
Internet	115.11	8.36	90	15	330	.0772
Work or Educational	210.78	19.08	135	0	1080	.1302
Gaming	64.67	8.79	15	0	540	.0435
Health	12.44	3.37	0	0	330	.0067
Other	334.44	20.94	270	0	1500	.2233
Total Smartphone use	1513.56	75.52	1260	390	5115	1.0000
Phase 2 (N = 136)						
Social Media	556.88	29.92	487.5	0	1665	.3789
Texting	144.26	10.17	90	0	540	.0966
Calling	95.29	7.54	67.5	15	330	.0632
Internet	118.79	7.35	90	15	330	.0846
Work or Educational	188.38	17.79	105	0	1020	.1151
Gaming	52.17	7.64	15	0	570	.0374
Health	9.7	2.49	0	0	210	.0051
Other	320.4	18.43	255	0	1020	.2191
Total Smartphone use	1485.88	72.45	1260	195	4125	1.0000

Note. The proportion of use is = [category use] / total smartphone use All values, except the proportion, represent estimated number of minutes of use per day

Table 6.

Correlation between subjective use at phase 1 & phase 2

Type of Use	**N**	**Pearson product**	***p***
Social Media	136	.559	.000
Texting	136	.647	.000
Calling	136	.591	.000
Internet Browsing	136	.273	.002
Work & Educational	136	.553	.000
Gaming	135	.708	.000
Health	135	.361	.000
Other	136	.561	.000
Total Smartphone	135	.526	.000

Note. All correlations evaluated while controlling for self-reported change in app use and smartphone use as well as the number of days between Phase 1 and Phase 2

Table 7. Correlations between objective and subjective use

Phase 1: Type of Use (n = 55)	***Spearman's P (rho)***	***p***
Social Media	.441	.001
Texting	.519	.000
Calling	.379	.004
Internet Browsing	.247	.069
Work & Educational	.097	.483
Gaming	.709	.000
Health	.472	.000
Other	.399	.003
Total Smartphone	.444	.001
Phase 2: Type of Use (n = 130)	**Spearman's *P* (rho)**	***p***
Social Media	.232	.008
Texting	.329	.000
Calling	.305	.000
Internet Browsing	.064	.473
Work & Educational	.031	.728
Gaming	.617	.000
Health	.288	.001
Other	.411	.000
Total Smartphone	.206	.019

Table 8. Objective Smartphone use and significant health outcome

		Physical Activity		
		b	*SE*	sr^2
Step 1	**Model Change**	**$\Delta R^2 = .026$, $\Delta F(3, 122) = 1.09$, $p = .357$**		
	Gender	-1.11	0.68	.021
	Financial Difficulty	0.00	0.00	.002
	Age	-0.07	0.21	.001
Step 2	**Model Change**	**$\Delta R^2 = .049$, $\Delta F(1, 121) = 6.47$, $p = .012$**		
	Gender	-0.92	0.67	.014
	Financial Difficulty	0.00	0.00	.004
	Age	-0.01	0.21	.000
	Total Smartphone use	0.01*	0.00	.049
	Total Model	**$R^2 = .076$, $F(4, 121) = 2.47$, $p = .048$**		

Note. p < .05*, p < .01**, p < .001***

Table 9. Objective Social media use and significant health outcome

		Outcome					
		Physical Activity			**IL-6**		
		b	*SE*	sr^2	*b*	*SE*	sr^2
Step 1	**Model Change**	**ΔR^2 = .026, ΔF(3, 122) = 1.09, *p* = .357**			**ΔR^2 = .352, ΔF(5, 102) = 11.06, *p* < .001**		
	BMI	-	-	-	2.28***	0.33	.304
	Physical Activity	-	-	-	-0.01*	0.01	.027
	Gender	-1.11	0.68	.021	0.12*	0.06	.030
	Financial Difficulty	0.00	0.00	.002	0.00	0.00	.003
	Age	-0.07	0.21	.001	0.03	0.02	.015
Step 2	**Model Change**	**ΔR^2 = .109, ΔF(2, 120) = 7.54, *p* = .001**			**ΔR^2 = .039, ΔF(2, 100) = 3.23, *p* = .044**		
	BMI	-	-	-	2.32***	0.33	.309
	Physical Activity	-	-	-	-0.02*	0.01	.028
	Gender	-0.74	0.66	.009	0.13*	0.05	.035
	Financial Difficulty	0.00	0.00	.005	0.00	0.00	.002
	Age	-0.04	0.20	.000	0.03*	0.02	.025
	Total SM use	0.35*	0.14	.045	0.03*	0.01	.030
	Proportion of SM	-9.46***	2.46	.107	-0.18	0.21	.004
Step 3	**Model Change**	**ΔR^2 = .060, ΔF(1, 119) = 8.82, *p* = .004**			**ΔR^2 = .000, ΔF(1, 99) = 0.05, *p* = .822**		
	BMI	-	-	-	2.32***	0.33	.309
	Physical Activity	-	-	-	-0.02	0.01	.023
	Gender	-0.85	0.64	.012	0.13*	0.05	.036
	Financial Difficulty	0.00	0.00	.003	0.00	0.00	.002
	Age	-0.07	0.20	.001	0.03*	0.02	.026
	Total SM use	0.321*	0.14	.037	0.03*	0.01	.031
	Proportion of SM	-10.58***	2.41	.130	-0.16	0.22	.003
	Interaction	-1.28**	0.43	.060	0.01	0.04	.000
	Total Model	**R^2 = .194, *F*(6, 119) = 4.79, *p* < .001**			**R^2 = .391, *F*(8, 99) = 7.96, *p* < .001**		

Note. SM = Social Media use. p < .05*, p < .01**, p < .001***

Table 10. Objective Texting use and significant health outcome

		Depression			Physical Activity			BMI		
		b	*SE*	sr^2	*b*	*SE*	sr^2	*b*	*SE*	sr^2
Step 1	**Model Change**	**ΔR^2 = .066, ΔF(3, 126) = 2.95, *p* = .035**			**ΔR^2 = .026, ΔF(3, 122) = 1.09, *p* = .357**			**ΔR^2 = .067, ΔF(4, 119) = 2.13, *p* = .082**		
	Physical Activity	-	-	-	-	-	-	0.00	0.00	.011
	Gender	0.81**	0.29	.059	-1.11	0.68	.021	-0.033*	0.02	.035
	Financial Difficulty	0.00	0.00	.008	0.00	0.00	.002	0.00	0.00	.001
	Age	0.10	0.09	.009	-0.07	0.21	.001	0.01	0.01	.008
Step 2	**Model Change**	**ΔR^2 = .012, ΔF(2, 124) = 0.80, *p* = .452**			**ΔR^2 = .086, ΔF(2, 120) = 5.78, *p* = .004**			**ΔR^2 = .085, ΔF(2, 117) = 5.85, *p* = .004**		
	Physical Activity	-	-	-	-	-	-	0.00	0.00	.020
	Gender	0.82**	0.29	.061	-1.16	0.66	.023	-0.03	0.02	.026
	Financial Difficulty	0.00	0.00	.006	0.00	0.00	.005	0.00	0.00	.000
	Age	0.09	0.09	.008	-0.02	0.20	.000	0.01	0.01	.009
	Total Text use	-0.17	0.49	.001	1.62	1.13	.015	0.05	0.03	.027
	Proportion of Text	-1.13	2.71	.001	3.46	6.18	.002	-0.452**	0.14	.075
Step 3	**Model Change**	**ΔR^2 = .056, ΔF(1, 123) = 7.90, *p* = .006**			**ΔR^2 = .064, ΔF(1, 119) = 9.23, *p* = .003**			**ΔR^2 = .000, ΔF(1, 116) = 0.05, *p* = .825**		
	Physical Activity	-	-	-	-	-	-	0.00	0.00	.017
	Gender	0.84**	0.28	.065	-1.07	0.64	.019	-0.03	0.02	.026
	Financial Difficulty	0.00	0.00	.004	0.00	0.00	.004	0.00	0.00	.000
	Age	0.08	0.09	.007	-0.04	0.20	.000	0.01	0.01	.009
	Total Text use	0.91	0.61	.015	4.24**	1.39	.065	0.06	0.03	.019
	Proportion of Text	-8.30*	3.67	.036	-14.00	8.29	.020	-0.48*	0.20	.044

Outcome: Depression, Physical Activity, BMI

Interaction	10.92**	3.89	.056	26.49**	8.72	.064	0.05	0.21	.000
Total Model	**R^2 = .133, *F*(6, 123) = 3.15, *p* = .007**			**R^2 = .176, *F*(6, 119) = 4.22, *p* = .001**			**R^2 = .152, *F*(7, 116) = 2.97, *p* = .007**		

Note. Text = texting use. p < .05*, p < .01**, p < .001***

Table 11. Objective Calling use and IL-6 inflammation

		IL-6		
		b	*SE*	sr^2
Step 1	**Model Change**	**ΔR^2 = .352, ΔF(5, 102) = 11.06, *p* < .001**		
	BMI	2.28***	0.33	.304
	Physical Activity	-0.01*	0.01	.027
	Gender	0.12*	0.06	.030
	Financial Difficulty	0.00	0.00	.003
	Age	0.03	0.02	.015
Step 2	**Model Change**	**ΔR^2 = .001, ΔF(2, 100) = 0.10, *p* = .909**		
	BMI	2.30***	0.34	.293
	Physical Activity	-0.01	0.01	.000
	Gender	0.12*	0.06	.030
	Financial Difficulty	0.00	0.00	.003
	Age	0.03	0.02	.015
	Total Call use	0.02	0.07	.000
	Proportion of Call use	-0.67	1.62	.001
Step 3	**Model Change**	**ΔR^2 = .048, ΔF(1, 99) = 7.97, *p* = .006**		
	BMI	2.18***	0.33	.258
	Physical Activity	-0.02*	0.01	.036
	Gender	0.12*	0.06	.027
	Financial Difficulty	0.00	0.00	.003
	Age	0.03	0.02	.019
	Total Call use	0.35*	0.14	.039
	Proportion of Call	-11.64**	4.19	.047
	Interaction	8.15**	2.89	.048
	Total Model	**R^2 = .401, F(8, 99) = 8.29, *p* < .001**		

Note. Call = calling Use. p < .05*, p < .01**, p < .001***

Table 12. Objective Internet use and IL-6 Inflammation

		IL-6		
		b	*SE*	sr^2
Step 1	**Model Change**	**$\Delta R^2 = .352, \Delta F(5, 102) = 11.06, p < .001$**		
	BMI	2.28***	0.33	.304
	Physical Activity	-0.01*	0.01	.027
	Gender	0.12*	0.06	.030
	Financial Difficulty	0.00	0.00	.003
	Age	0.03	0.02	.015
Step 2	**Model Change**	**$\Delta R^2 = .033, \Delta F(2, 100) = 2.66, p = .075$**		
	BMI	2.33***	0.33	.315
	Physical Activity	-0.02*	0.01	.030
	Gender	0.12*	0.05	.030
	Financial Difficulty	0.00	0.00	.002
	Age	0.03*	0.02	.025
	Total NET	0.05*	0.02	.032
	Proportion of NET	-2.76*	1.31	.027
Step 3	**Model Change**	**$\Delta R^2 = .000, \Delta F(1, 99) = 0.45, p = .832$**		
	BMI	2.33***	0.33	.314
	Physical Activity	-0.02*	0.01	.029
	Gender	0.12*	0.05	.031
	Financial Difficulty	0.00	0.00	.002
	Age	0.03*	0.02	.025
	Total NET	0.05*	0.02	.027
	Proportion of NET	-2.54	1.67	.014
	Interaction	-0.09	0.41	.000
	Total Model	**$R^2 = .385, F(8, 99) = 7.73, p < .001$**		

Note. Net = Internet Use. p < .05*, p < .01**, p < .001***

Table 13. Objective Work or education use and Depression

		Depression		
		b	*SE*	sr^2
Step 1	**Model Change**	**ΔR^2 = .066, ΔF(3, 126) = 2.95, *p* = .035**		
	Gender	0.81**	0.29	.059
	Financial Difficulty	0.00	0.00	.008
	Age	0.10	0.09	.009
Step 2	**Model Change**	**ΔR^2 = .018, ΔF(2, 124) =1.21, *p* = .301**		
	Gender	0.84**	0.29	.064
	Financial Difficulty	0.00	0.00	.009
	Age	0.09	0.09	.008
	Total WEP	0.05	0.36	.000
	Proportion of WEP	-9.18	7.34	.011
Step 3	**Model Change**	**ΔR^2 = .037, ΔF(1, 123) = 5.11, *p* = .026**		
	Gender	0.85**	0.28	.065
	Financial Difficulty	0.00	0.00	.010
	Age	0.10	0.09	.009
	Total WEP	0.17	0.36	.002
	Proportion of WEP	-20.92*	8.90	.040
	Interaction	25.70*	11.37	.036
	Total Model	**R^2 = .120, *F*(6, 123) = 2.80, *p* = .014**		

Note. WEP = Work or Educational Use. p < .05*, p < .01**, p < .001***

Table 14. Objective Game use and IL-6

		IL-6		
		b	*SE*	sr^2
Step 1	**Model Change**	**ΔR^2 = .352, ΔF(5, 102) = 11.06, p < .001**		
	BMI	2.28***	0.33	.304
	Physical Activity	-0.01*	0.01	.027
	Gender	0.12*	0.06	.030
	Financial Difficulty	0.00	0.00	.003
	Age	0.03	0.02	.015
Step 2	**Model Change**	**ΔR^2 = .050, ΔF(2, 100) = 4.19, p = .018**		
	BMI	2.33***	0.32	.315
	Physical Activity	-0.02*	0.01	.035
	Gender	0.10	0.06	.016
	Financial Difficulty	0.00	0.00	.004
	Age	0.02	0.02	.009
	Total Game	0.15	0.08	.019
	Proportion of Game	-5.64**	2.08	.044
Step 3	**Model Change**	**ΔR^2 = .003, ΔF(1, 99) = 0.45, p = .505**		
	BMI	2.31***	0.32	.306
	Physical Activity	-0.02*	0.01	.035
	Gender	0.09	0.06	.016
	Financial Difficulty	0.00	0.00	.003
	Age	0.02	0.02	.009
	Total Game	0.20	0.11	.018
	Proportion of Game	-9.17	5.67	.016
	Interaction	2.76	4.13	.003
	Total Model	**R^2 = .404, F(8, 99) = 8.40, p < .001**		

Note. p < .05*, p < .01**, p < .001***

Table 15. Subjective Smartphone use and IL-6

		IL-6		
		b	*SE*	sr^2
Step 1	**Model Change**	**$\Delta R^2 = .349$, $\Delta F(5, 108) = 11.59$, $p < .001$**		
	BMI	2.31***	0.32	.307
	Physical Activity	-0.01	0.01	.023
	Gender	0.10*	0.05	.024
	Financial Difficulty	0.00	0.00	.003
	Age	0.03	0.02	.014
Step 2	**Model Change**	**$\Delta R^2 = .034$, $\Delta F(1, 107) = 5.92$, $p = .017$**		
	BMI	2.31***	0.32	.308
	Physical Activity	-0.02*	0.01	.032
	Gender	0.09	0.05	.015
	Financial Difficulty	0.00	0.00	.006
	Age	0.02	0.02	.011
	Total Smartphone use	0.01*	0.00	.034
	Total Model	**$R^2 = .383$, $F(6, 107) = 11.09$, $p < .001$**		

Note. p < .05*, p < .01**, p < .001***

Table 16. Subjective Social media use and significant health outcomes

		Trait Anxiety			Physical Activity			Neck Pain			IL-6		
		b	*SE*	sr^2	*b*	*SE*	sr^2	*b*	*SE*	sr^2	*b*	*SE*	sr^2
Step 1	**Model Change**	**ΔR^2 = .056, ΔF(3, 132) = 2.60, *p* = .055**			**ΔR^2 = .025, ΔF(3, 128) = 1.12, *p* = .345**			**ΔR^2 = .143, ΔF(3, 132) = 7.32, *p* < .001**			**ΔR^2 = .349, ΔF(5, 108) = 11.59, *p* < .001**		
	BMI	-	-	-	-	-	-	-	-	-	2.31***	0.32	.307
	Physical Activity	-	-	-	-	-	-	-	-	-	-0.01	0.01	.023
	Gender	4.90*	1.88	.049	-1.08	0.66	.020	0.10*	0.04	.042	0.10*	0.05	.024
	Financial Difficulty	0.00	0.01	.000	0.00	0.00	.002	0.00**	0.00	.054	0.00	0.00	.003
	Age	-0.24	0.60	.001	-0.08	0.21	.001	0.04***	0.01	.083	0.03	0.02	.014
Step 2	**Model Change**	**ΔR^2 = .046, ΔF(2, 130) = 3.30, *p* = .040**			**ΔR^2 = .081, ΔF(2, 126) = 5.74, *p* = .004**			**ΔR^2 = .063, ΔF(2, 130) = 5.17, *p* = .007**			**ΔR^2 = .048, ΔF(2, 106) = 4.27, *p* = .017**		
	BMI	-	-	-	-	-	-	-	-	-	2.35***	0.32	.312
	Physical Activity	-	-	-	-	-	-	-	-	-	-0.02*	0.01	.029
	Gender	4.19*	1.87	.035	-0.91	0.65	.014	0.08*	0.04	.027	0.08	0.05	.015
	Financial Difficulty	0.00	0.01	.000	0.00	0.00	.001	0.00**	0.00	.055	0.00	0.00	.003
	Age	-0.29	0.59	.002	-0.05	0.20	.000	0.04***	0.01	.078	0.02	0.02	.011
	Total SM	0.05	0.12	.001	0.10*	0.04	.039	0.00	0.00	.002	0.01**	0.00	.042
	Proportion of SM	21.34*	9.66	.034	-10.33 **	3.29	.070	0.52**	0.19	.045	-0.03	0.29	.000
Step 3	**Model Change**	**ΔR^2 = .001, ΔF(1, 129) = 0.09, *p* = .764**			**ΔR^2 = .007, ΔF(1, 125) = 0.99, *p* = .322**			**ΔR^2 = .004, ΔF(1, 129) = 0.71, *p* = .400**			**ΔR^2 = .000, ΔF(1, 105) = 0.02, *p* = .878**		
	BMI	-	-	-	-	-	-	-	-	-	2.35***	0.32	.311
	Physical Activity	-	-	-	-	-	-	-	-	-	-0.02*	0.01	.029

Gender	4.24*	1.88	.035	-0.97	0.65	.016	0.08*	0.04	.029	0.08	0.05	.014
Financial Difficulty	0.00	0.01	.000	0.00	0.00	.001	0.00**	0.00	.056	0.00	0.00	.003
Age	-0.30	0.59	.002	-0.05	0.20	.000	0.04***	0.01	.078	0.02	0.02	.011
Total SM	0.05	0.12	.001	0.10*	0.04	.038	0.00	0.00	.002	0.01**	0.00	.041
Proportion of SM	21.87*	9.86	.034	-10.97**	3.35	.076	0.55**	0.20	.048	-0.04	0.30	.000
Interaction	0.35	1.15	.001	-0.39	0.39	.007	0.02	0.02	.004	-0.01	0.03	.000
Total Model	**R^2 = .102, F(6, 129) = 2.44, p = .029**			**R^2 = .114, F(6, 125) = 2.68, p = .018**			**R^2 = .210, F(6, 129) = 5.72, p < .001**			**R^2 = .398, F(8, 105) = 8.67, p < .001**		

Note. SM = Social media. p < .05*, p < .01**, p < .001***

Table 17. Subjective Texting use and significant health outcomes

		Outcome								
		Depression			**IL-6**			**CRP**		
		b	*SE*	sr^2	*b*	*SE*	sr^2	*b*	*SE*	sr^2
Step 1	**Model Change**	**$\Delta R^2 = .062, \Delta F(3, 132) = 2.93, p = .036$**			**$\Delta R^2 = .349, \Delta F(5, 108) = 11.59, p < .001$**			**$\Delta R^2 = .209, \Delta F(5, 105) = 5.56, p < .001$**		
	BMI	-	-	-	2.31***	0.32	.307	3.19***	0.64	.185
	Physical Activity	-	-	-	-0.01	0.01	.023	-0.03	0.01	.024
	Gender	0.79**	0.28	.056	0.10*	0.05	.024	-0.03	0.11	.001
	Financial Difficulty	0.00	0.00	.008	0.00	0.00	.003	0.00	0.00	.007
	Age	0.10	0.09	.010	0.03	0.02	.014	-0.07*	0.04	.031
Step 2	**Model Change**	**$\Delta R^2 = .038, \Delta F(2, 130) = 2.74, p = .069$**			**$\Delta R^2 = .037, \Delta F(2, 106) = 3.21, p = .044$**			**$\Delta R^2 = .035, \Delta F(2, 103) = 2.39, p = .096$**		
	BMI	-	-	-	2.34***	0.32	.310	3.30***	0.64	.194
	Physical Activity	-	-	-	-0.02*	0.01	.033	-0.03*	0.01	.037
	Gender	0.79**	0.28	.056	0.08	0.05	.014	-0.07	0.11	.003
	Financial Difficulty	0.00	0.00	.004	0.00	0.00	.007	0.00	0.00	.013
	Age	0.09	0.09	.008	0.03	0.02	.014	-0.07	0.04	.026
	Total Text	0.05	0.04	.013	0.02*	0.01	.036	0.03*	0.02	.034
	Proportion of Text	-17.64*	7.72	.036	-2.98*	1.40	.026	-3.89	2.82	.014
Step 3	**Model Change**	**$\Delta R^2 = .002, \Delta F(1, 129) = 0.319, p = .573$**			**$\Delta R^2 = .008, \Delta F(1, 105) = 1.39, p = .242$**			**$\Delta R^2 = .015, \Delta F(1, 102) = 2.02, p = .158$**		
	BMI	-	-	-	2.36***	0.32	.314	3.34***	0.64	.198
	Physical Activity	-	-	-	-0.02*	0.01	.034	-0.03*	0.01	.038
	Gender	0.78**	0.28	.053	0.09	0.05	.016	-0.06	0.11	.002
	Financial Difficulty	0.00	0.00	.004	0.00	0.00	.008	0.00	0.00	.014
	Age	0.09	0.09	.008	0.03	0.02	.014	-0.07	0.03	.026
	Total Text	0.05	0.04	.011	0.02**	0.01	.040	0.03*	0.02	.040
	Proportion of Text	-16.62*	7.95	.030	-3.33*	1.43	.031	-4.68	2.86	.020
	Interaction	-0.64	1.14	.002	0.23	0.20	.008	0.55	0.39	.015
	Total Model	**$R^2 = .103, F(6, 129) = 2.46, p = .028$**			**$R^2 = .394, F(8, 105) = 8.55\ p < .001$**			**$R^2 = .259, F(8, 102) = 4.46\ p < .001$**		

Note. Text = Texting on smartphone. p < .05*, p < .01**, p < .001***

Table 18. Subjective Calling and significant health outcomes

		Outcome								
		Depression			WHR			IL-6		
		b	*SE*	sr^2	*b*	*SE*	sr^2	*b*	*SE*	sr^2
Step 1	**Model Change**	**$\Delta R^2 = .062$, $\Delta F(3, 132) = 2.93$, $p = .036$**			**$\Delta R^2 = .231$, $\Delta F(4, 124) = 9.32$, $p < .001$**			**$\Delta R^2 = .349$, $\Delta F(5, 108) = 11.59$, $p < .001$**		
	BMI	-	-	-	-	-	-	2.31***	0.32	.307
	Physical Activity	-	-	-	0.00	0.00	.003	-0.01	0.01	.023
	Gender	0.79**	0.28	.056	-0.06***	0.01	.199	0.10*	0.05	.024
	Financial Difficulty	0.00	0.00	.008	0.00	0.00	.001	0.00	0.00	.003
	Age	0.10	0.09	.010	0.00	0.00	.003	0.03	0.02	.014
Step 2	**Model Change**	**$\Delta R^2 = .040$, $\Delta F(2, 130) = 2.88$, $p = .060$**			**$\Delta R^2 = .038$, $\Delta F(2, 122) = 3.15$, $p = .046$**			**$\Delta R^2 = .045$, $\Delta F(2, 106) = 3.97$, $p = .022$**		
	BMI	-	-	-	-	-	-	2.38***	0.32	.316
	Physical Activity	-	-	-	0.00	0.00	.001	-0.02*	0.01	.037
	Gender	0.73*	0.28	.046	-0.06***	0.01	.171	0.09	0.05	.017
	Financial Difficulty	0.00	0.00	.001	0.00	0.00	.001	0.00	0.00	.006
	Age	0.10	0.09	.009	0.00	0.00	.003	0.02	0.02	.010
	Total Call	0.01*	0.00	.040	0.00	0.00	.002	0.00**	0.00	.042
	Proportion of Call	-16.63	9.96	.019	-0.80*	0.37	.028	-4.47*	1.81	.035
Step 3	**Model Change**	**$\Delta R^2 = .000$, $\Delta F(1, 129) = 0.00$, $p = .951$**			**$\Delta R^2 = .002$, $\Delta F(1, 121) = .40$, $p = .530$**			**$\Delta R^2 = .001$, $\Delta F(1, 106) = 0.14$, $p = .706$**		
	BMI	-	-	-	-	-	-	2.39***	0.32	.315
	Physical Activity	-	-	-	0.00	0.00	.001	-0.02*	0.01	.036
	Gender	0.73*	0.28	.046	-0.06***	0.01	.170	0.09	0.05	.018
	Financial Difficulty	0.00	0.00	.001	0.00	0.00	.001	0.00	0.00	.006
	Age	0.10	0.09	.009	0.00	0.00	.003	0.02	0.02	.010
	Total Call	0.01*	0.00	.034	0.00	0.00	.001	0.00**	0.00	.040

Proportion of Call	-16.64	10.00	.019	-0.80*	0.37	.028	-4.48*	1.82	.035
Interaction	-0.01	0.10	.000	0.00	0.00	.002	-0.01	0.02	.001
Total Model	**R^2 = .102, *F*(6, 129) = 2.45, *p* = .028**			**R^2 = .271, *F*(7, 121) = 6.436, *p* < .001**			**R^2 = .395, *F*(8, 105) = 8.59 *p* < .001**		

Note. Call = Calling. p < .05*, p < .01**, p < .001***

Table 19. Subjective Internet browsing and significant health outcomes

		Outcome														
		Depression			**Physical Symptoms**			**Vision Problems**			**IL-6**			**CRP**		
		b	*SE*	sr^2	*b*	*SE*	sr^2	*b*	*SE*	sr^2	*b*	*SE*	sr^2	*b*	*SE*	sr^2
Step 1	**Model Change**	**$\Delta R^2 = .062$, $\Delta F(3, 132) = 2.93$, $p = .036$**			**$\Delta R^2 = .119$, $\Delta F(3, 132) = 5.93$, $p = .001$**			**$\Delta R^2 = .055$, $\Delta F(3, 132) = 2.57$, $p = .057$**			**$\Delta R^2 = .349$, $\Delta F(5, 108) = 11.59$, $p < .001$**			**$\Delta R^2 = .209$, $\Delta F(5, 105) = 5.56$, $p < .001$**		
	BMI	-	-	-	-	-	-	-	-	-	2.310***	0.32	0.306916	3.188***	0.64	.185
	Physical Activity	-	-	-	-	-	-	-	-	-	-0.01	0.01	0.0225	-0.03	0.01	.024
	Gender	0.786**	0.28	.056	1.211***	0.30	.113	0.136**	0.05	.050	0.104*	0.05	.024	-0.03	0.11	.001
	Financial Difficulty	0.00	0.00	.008	0.00	0.00	.005	0.00	0.00	.005	0.00	0.00	.003	0.00	0.00	.007
	Age	0.10	0.09	.010	0.13	0.09	.013	0.02	0.02	.009	0.03	0.02	.014	-0.07*	0.04	.031
Step 2	**Model Change**	**$\Delta R^2 = .031$, $\Delta F(2, 130) = 2.21$, $p = .114$**			**$\Delta R^2 = .037$, $\Delta F(2, 130) = 2.84$, $p = .062$**			**$\Delta R^2 = .007$, $\Delta F(2, 130) = 0.48$, $p = .620$**			**$\Delta R^2 = .061$, $\Delta F(2, 106) = 5.47$, $p = .006$**			**$\Delta R^2 = .039$, $\Delta F(2, 103) = 2.68$, $p = .073$**		
	BMI	-	-	-	-	-	-	-	-	-	2.279***	0.31	.546	3.119***	0.63	.176
	Physical Activity	-	-	-	-	-	-	-	-	-	-0.015*	0.01	-.174	-0.03	0.01	.027
	Gender	0.748**	0.28	.050	1.159***	0.29	.103	0.136**	0.05	.049	0.08	0.05	.015	-0.05	0.10	.001
	Financial Difficulty	0.00	0.00	.003	0.00	0.00	.002	0.00	0.00	.002	0.00	0.00	.004	0.00	0.00	.005
	Age	0.11	0.09	.010	0.14	0.09	.015	0.02	0.02	.008	0.02	0.02	.011	-0.069*	0.03	.030
	Total Net use	0.07	0.04	.020	0.07	0.04	.015	0.01	0.01	.006	0.016*	0.01	.026	0.01	0.02	.002
	Proportion of Net use	-6.46*	3.25	.028	-8.073*	3.40	.037	-0.19	0.61	.001	-1.858***	0.56	.061	-2.416*	1.15	.032
Step 3	**Model Change**	**$\Delta R^2 = .002$, $\Delta F(1, 129) = 0.298$, $p = .209$**			**$\Delta R^2 = .021$, $\Delta F(1, 129) = 3.34$, $p = .070$**			**$\Delta R^2 = .033$, $\Delta F(1, 129) = 4.74$, $p = .031$**			**$\Delta R^2 = .001$, $\Delta F(1, 105) = 0.98$, $p = .755$**			**$\Delta R^2 = .003$, $\Delta F(1, 102) = 0.46$, $p = .497$**		
	BMI	-	-	-	-	-	-	-	-	-	2.275***	0.31	.297	3.137***	0.64	.178

Physical Activity	-	-	-	-	-	-	-	-	-	-0.015*	0.01	.030	-0.03	0.01	.027
Gender	0.757**	0.28	.051	1.19***	0.29	.108	0.143**	0.05	.054	0.08	0.05	.014	-0.04	0.11	.001
Financial Difficulty	0.00	0.00	.003	0.00	0.00	.001	0.00	0.00	.001	0.00	0.00	.004	0.00	0.00	.007
Age	0.11	0.09	.010	0.14	0.09	.016	0.02	0.02	.008	0.02	0.02	.011	-0.07*	0.03	.030
Total Net use	0.08	0.04	.022	0.08	0.04	.020	0.01	0.01	.011	0.016*	0.01	.025	0.01	0.02	.002
Proportion of Net use	-6.878*	3.35	.030	-9.517**	3.46	.048	-0.50	0.62	.004	-1.817**	0.58	.055	-2.607*	1.19	.035
Interaction	0.44	0.81	.002	1.52	0.83	.021	0.322*	0.15	.033	-0.05	0.14	.001	0.20	0.29	.003
Total Model	**R^2 = .095, F(6, 129) = 2.27, p = .041**			**R^2 = .177, F(6, 129) = 4.62, p < .001**			**R^2 = .095, F(6, 129) = 2.27, p = .041**			**R^2 = .411, F(8, 105) = 9.15 p < .001**			**R^2 = .252, F(8, 102) = 4.29 p < .001**		

Note. Net = Internet Use. p < .05*, p < .01**, p < .001***

Table 20. Subjective Work or Educational use and significant health outcomes

		Outcome											
		Physical Symptoms			**Physical Activity**			**Neck Pain**			**IL-6**		
		b	*SE*	sr^2	*b*	*SE*	sr^2	*b*	*SE*	sr^2	*b*	*SE*	sr^2
Step 1	**Model Change**	**ΔR^2 = .119, $\Delta F(3, 132)$ = 5.93, *p* = .001**			**ΔR^2 = .025, $\Delta F(3, 128)$ = 1.12, *p* = .345**			**ΔR^2 = .143, $\Delta F(3, 132)$ = 7.32, *p* < .001**			**ΔR^2 = .349, $\Delta F(5, 108)$ = 11.59, *p* < .001**		
	BMI	-	-	-	-	-	-	-	-	-	2.31***	0.32	.307
	Physical Activity	-	-	-	-	-	-	-	-	-	-0.01	0.01	.023
	Gender	1.21***	0.30	.113	-1.08	0.66	.020	0.10*	0.04	.042	0.10*	0.05	.024
	Financial Difficulty	0.00	0.00	.005	0.00	0.00	.002	0.00**	0.00	.054	0.00	0.00	.003
	Age	0.13	0.09	.013	-0.08	0.21	.001	0.04***	0.01	.083	0.03	0.02	.014
Step 2	**Model Change**	**ΔR^2 = .034, $\Delta F(2, 130)$ = 2.60, *p* = .078**			**ΔR^2 = .066, $\Delta F(2, 126)$ = 4.57, *p* = .012**			**ΔR^2 = .037, $\Delta F(2, 130)$ = 2.96, *p* = .055**			**ΔR^2 = .027, $\Delta F(2, 106)$ = 2.25, *p* = .110**		
	BMI	-	-	-	-	-	-	-	-	-	2.31***	0.32	.306
	Physical Activity	-	-	-	-	-	-	-	-	-	-0.02*	0.01	.034
	Gender	1.14***	0.29	.099	-1.29*	0.65	.029	0.09*	0.04	.034	0.09	0.05	.015
	Financial Difficulty	0.00	0.00	.002	0.00	0.00	.001	0.00**	0.00	.048	0.00	0.00	.004
	Age	0.14	0.09	.015	-0.07	0.20	.001	0.04***	0.01	.088	0.02	0.02	.012
	Total WEP	0.06	0.03	.020	0.20**	0.07	.052	0.01	0.00	.010	0.01	0.01	.023
	Proportion of WEP	-5.89*	2.59	.034	-16.79**	5.65	.064	-0.75*	0.33	.033	-0.90*	0.44	.024
Step 3	**Model Change**	**ΔR^2 = .001, $\Delta F(1, 129)$ = 0.218, *p* = .641**			**ΔR^2 = .012, $\Delta F(1, 125)$ = 1.63, *p* = .204**			**ΔR^2 = .000, $\Delta F(2, 130)$ = 0.043, *p* = .836**			**ΔR^2 = .009, $\Delta F(1, 105)$ = 1.51, *p* = .222**		
	BMI	-	-	-	-	-	-	-	-	-	2.30***	0.32	.303
	Physical Activity	-	-	-	-	-	-	-	-	-	-0.02*	0.01	.036
	Gender	1.13***	0.30	.095	-1.39*	0.65	.033	0.09*	0.04	.033	0.08	0.05	.012
	Financial Difficulty	0.00	0.00	.002	0.00	0.00	.002	0.00**	0.00	.048	0.00	0.00	.003
	Age	0.14	0.09	.014	-0.10	0.20	.002	0.04***	0.01	.087	0.02	0.02	.011
	Total WEP	0.06	0.03	.022	0.22**	0.08	.061	0.01	0.00	.011	0.01*	0.01	.027

Proportion of WEP	-5.63*	2.66	.030	-15.32**	5.75	.051	-0.74*	0.34	.030	-0.77	0.45	.017
Interaction	-0.11	0.24	.001	-0.65	0.51	.012	-0.01	0.03	.000	-0.05	0.04	.009
Total Model	**R^2 = .154, *F*(6, 129) = 3.91, *p* = .001**			**R^2 = .103, *F*(6, 125) = 2.40, *p* = .032**			**R^2 = .180, *F*(6, 129) = 4.73, *p* < .001**			**R^2 = .385, *F*(8, 105) = 8.21 *p* < .001**		

Note. WEP = Work or Educational Use. p < .05*, p < .01**, p < .001***

Table 21. Subjective Game use and significant health outcomes

		Outcome																	
		Perceived Stress			**Depression**			**Physical Symptoms**			**WHR**			**BMI**			**CRP**		
		b	*SE*	sr^2	*b*	*SE*	sr^2	*b*	*SE*	sr^2	*b*	*SE*	sr^2	*b*	*SE*	sr^2	*b*	*SE*	sr^2
Step 1	**Model Change**	**ΔR^2 = .084, ΔF(3, 132) = 4.03, *p* = .009**			**ΔR^2 = .062, ΔF(3, 132) = 2.93, *p* = .036**			**ΔR^2 = .119, ΔF(3, 132) = 5.93, *p* = .001**			**ΔR^2 = .231, ΔF(4, 124) = 9.32, *p* < .001**			**ΔR^2 = .062, ΔF(4, 125) = 2.05, *p* = .092**			**ΔR^2 = .209, ΔF(5, 105) = 5.56, *p* < .001**		
	BMI	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	3.19***	0.64	.185
	Physical Activity	-	-	-	-	-	-	-	-	-	0.00	0.00	.003	0.00	0.00	.017	-0.03	0.01	.024
	Gender	4.03**	1.16	.084	0.79**	0.28	.056	1.21***	0.30	.113	-0.06***	0.01	.199	-0.03	0.02	.023	-0.03	0.11	.001
	Financial Difficulty	0.00	0.01	.002	0.00	0.00	.008	0.00	0.00	.005	0.00	0.00	.001	0.00	0.00	.001	0.00	0.00	.007
	Age	0.04	0.37	.000	0.10	0.09	.010	0.13	0.09	.013	0.00	0.00	.003	0.01	0.01	.009	-0.07*	0.04	.031
Step 2	**Model Change**	**ΔR^2 = .042, ΔF(2, 130) = 3.10, *p* = .049**			**ΔR^2 = .077, ΔF(2, 130) = 5.82, *p* = .004**			**ΔR^2 = .040, ΔF(2, 130) = 3.09, *p* = .049**			**ΔR^2 = .045, ΔF(2, 122) = 3.78, *p* = .025**			**ΔR^2 = .041, ΔF(2, 123) = 2.78, *p* = .066**			**ΔR^2 = .032, ΔF(2, 103) = 2.16, *p* = .121**		
	BMI	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	2.97***	0.65	.155
	Physical Activity	-	-	-	-	-	-	-	-	-	0.00	0.00	.001	0.00	0.00	.013	-0.02	0.01	.023
	Gender	4.34***	1.18	.091	0.95**	0.28	.077	1.33***	0.30	.127	-0.06***	0.01	.160	-0.02	0.02	.015	-0.03	0.11	.000
	Financial Difficulty	0.00	0.00	.002	0.00	0.00	.008	0.00	0.00	.005	0.00	0.00	.000	0.00	0.00	.000	0.00	0.00	.012
	Age	-0.09	0.37	.000	0.07	0.09	.004	0.10	0.09	.008	0.00	0.00	.001	0.00	0.01	.004	-0.08*	0.04	.040
	Total Game	2.12*	0.87	.040	0.60**	0.21	.057	0.49*	0.22	.032	0.02**	0.01	.040	0.03*	0.01	.038	0.16*	0.08	.030
	Proportion of Game	-21.18	14.23	.015	-3.50	3.36	.007	-3.44	3.60	.006	-0.17	0.13	.011	-0.24	0.18	.013	-2.37	1.30	.025
Step 3	**Model Change**	**ΔR^2 = .007, ΔF(1, 129) = 1.08, *p* = .301**			**ΔR^2 = .002, ΔF(1, 129) = 0.253, *p* = .616**			**ΔR^2 = .000, ΔF(1, 129) = 0.074, *p* = .785**			**ΔR^2 = .001, ΔF(1, 121) = 0.14, *p* = .706**			**ΔR^2 = .005, ΔF(1, 122) = 0.75, *p* = .389**			**ΔR^2 = .000, ΔF(1, 102) = 0.02, *p* = .895**		
	BMI	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	2.97	0.65	.155

Physical Activity	-	-	-	-	-	-	-	-	-	0.00	0.00	.001	0.00	0.00	.014	-0.02	0.01	.023
Gender	4.19**	1.19	.083	0.93**	0.28	.073	1.32***	0.30	.123	-0.06***	0.01	.160	-0.02	0.02	.012	-0.03	0.11	.000
Financial Difficulty	0.00	0.00	.001	0.00	0.00	.008	0.00	0.00	.004	0.00	0.00	.000	0.00	0.00	.000	0.00	0.00	.012
Age	-0.09	0.37	.000	0.07	0.09	.004	0.10	0.09	.008	0.00	0.00	.001	0.00	0.01	.004	-0.08*	0.04	.040
Total Game	3.45*	1.55	.033	0.76*	0.37	.028	0.58	0.39	.014	0.03	0.01	.019	0.01	0.02	.003	0.18	0.14	.013
Proportion of Game	-62.30	42.11	.015	-8.23	9.99	.004	-6.18	10.70	.002	-0.30	0.37	.004	0.19	0.53	.001	-2.82	3.63	.004
Interaction	28.92	27.88	.007	3.32	6.61	.002	1.93	7.08	.000	0.09	0.25	.001	-0.30	0.35	.005	0.32	2.39	.000
Total Model	**R^2 = .133, F(6, 129) = 3.29, p = .005**			**R^2 = .141, F(6, 129) = 3.53, p = .003**			**R^2 = .159, F(6, 129) = 4.07, p = .001**			**R^2 = .277, F(7, 121) = 6.62, p < .001**			**R^2 = .108, F(7, 122) = 2.10, p = .048**			**R^2 = .241, F(8, 102) = 4.06 p < .001**		

Note. p < .05*, p < .01**, p < .001***

Figures

Predictors

Step 1:
- CV(s)

Step 2:
- Total [category] time
- [category] proportion

Step 3:
- Total [category] time **X** [category] proportion

Outcome

Mental health
- Depression
- Stress
- Anxiety
  - State
  - Trait

Physical Health
- Sleep
  - Overall sleep quality
  - Sleep latency
  - Sleep duration
- Obesity
  - WHR
  - BMI
- Physical activity
- Physical symptoms
  - Overall physical symptoms
  - Vision problems
  - Hearing problems
  - Neck pain
  - Back pain
- Inflammation
  - IL-6
  - CRP

Figure 1. Regression model used to determine how objective and subjective categories of smartphone use related to health.

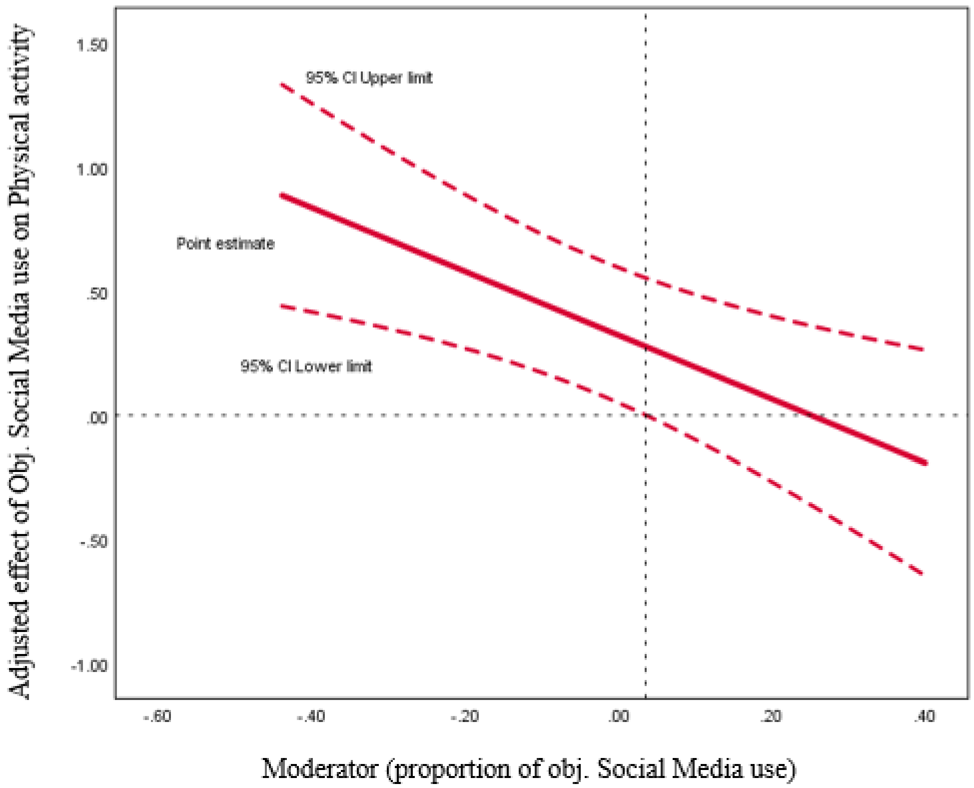

Figure 2. Johnson-Neyman values and CI's for the interaction of social media use on physical activity. Variables in the plot are mean centered. At the original social media proportion of .4735 and below (55.56% of the sample), the effect of objective social media use on physical activity became significant and more positive as the moderator decreased. Obj. = Objective measures of use.

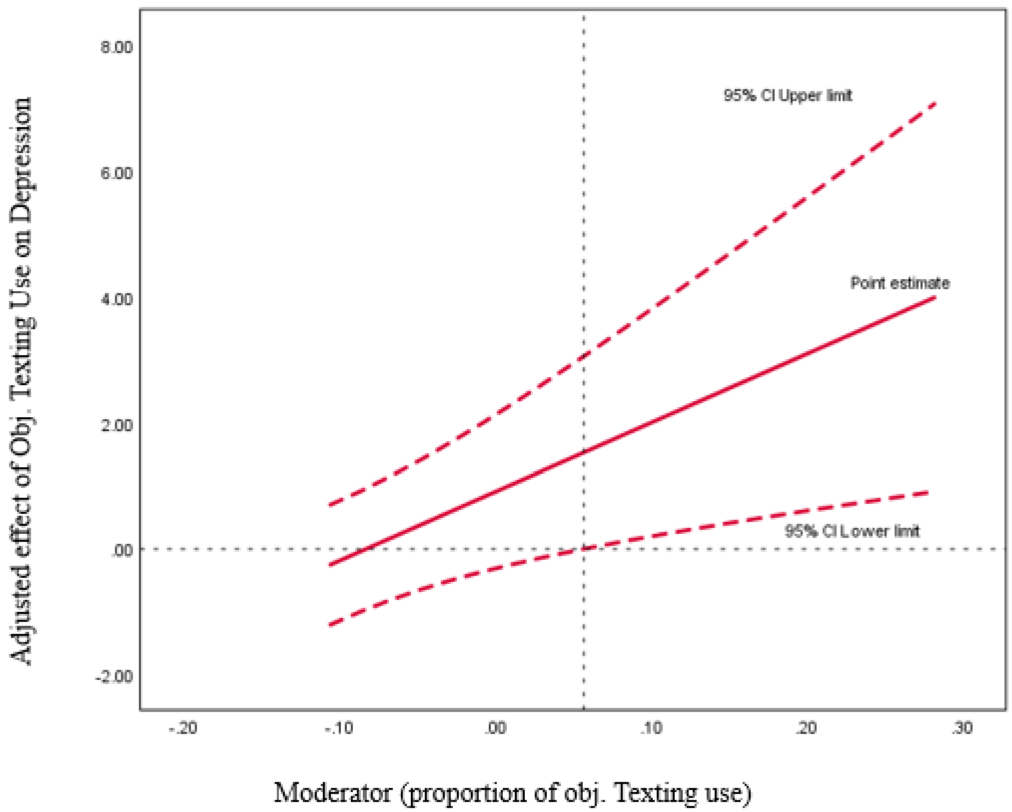

Figure 3. Johnson-Neyman values and CI's. Variables in the plot are mean centered. At the original texting proportion of .1624 and above (24.62% of the sample), the adjusted effect of objective texting on depression became significant and more positive as the moderator increases. Obj. = Objective measures of use.

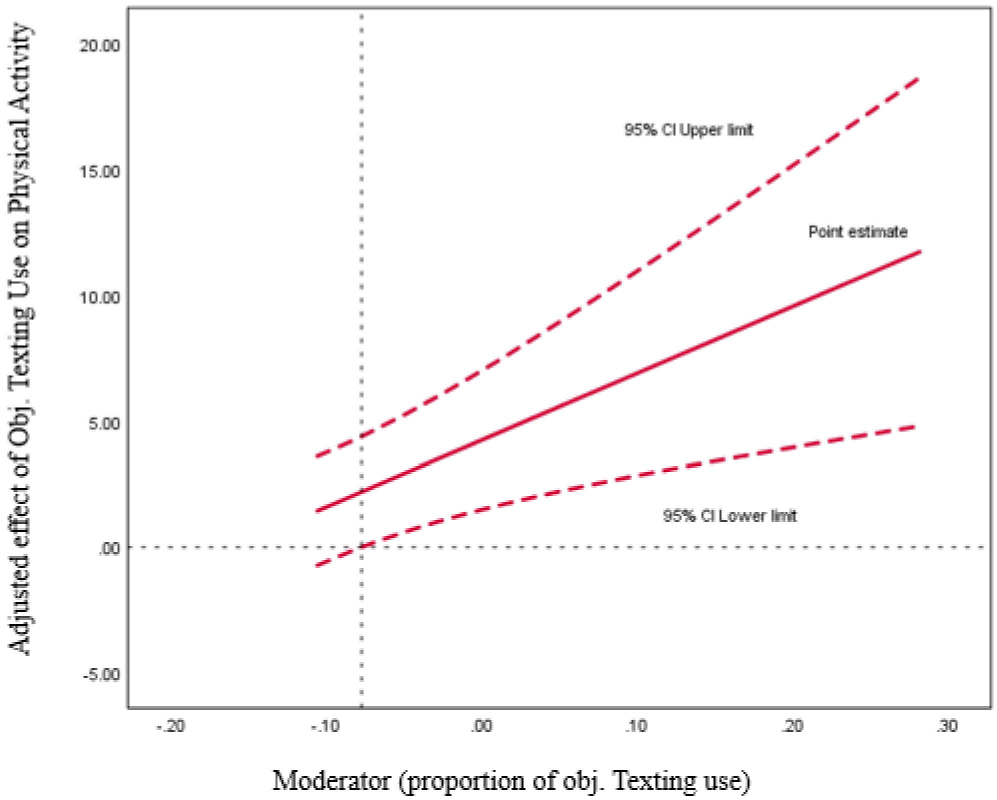

Figure 4. Johnson-Neyman values and CI's. Variables in the plot are mean centered. At the original texting proportion of .0283 and above (78.57% of the sample), the adjusted effect of objective texting on physical activity became significant and more positive as the moderator increases. Obj. = Objective measures of use.

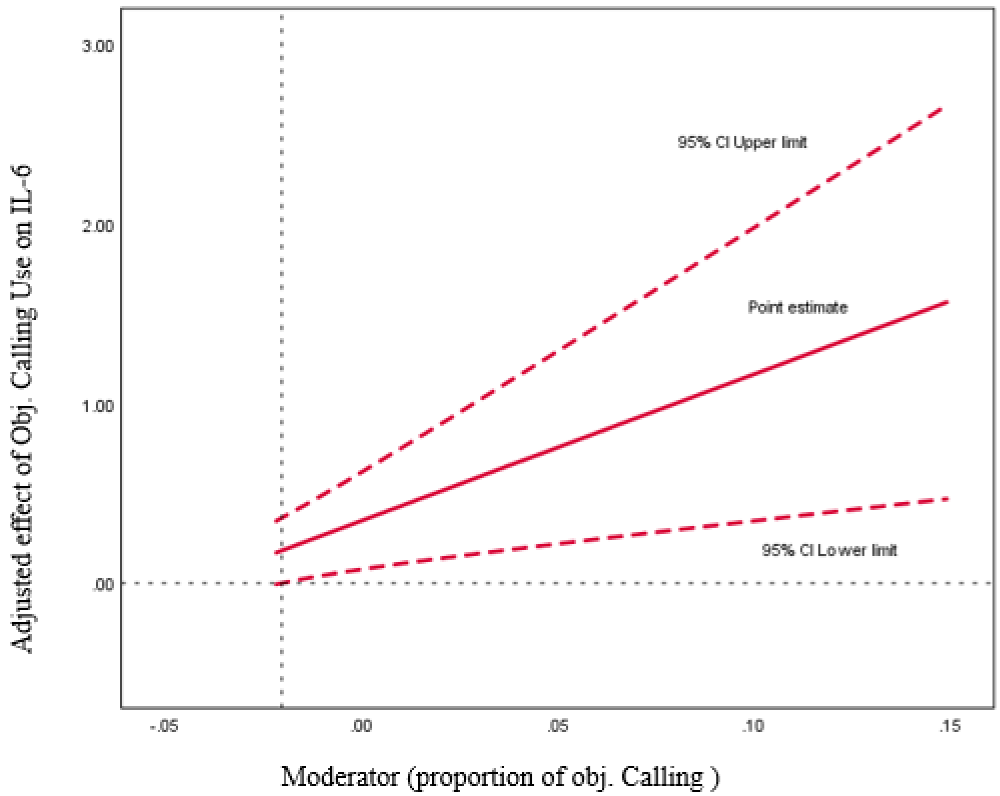

Figure 5. Johnson-Neyman values and CI's. Variables in the plot are mean centered. At the original calling proportion of .0032 and above (66.67% of the sample), the adjusted effect of objective calling on IL-6 became significant and more positive as the moderator increases. Obj. = Objective measures of use.

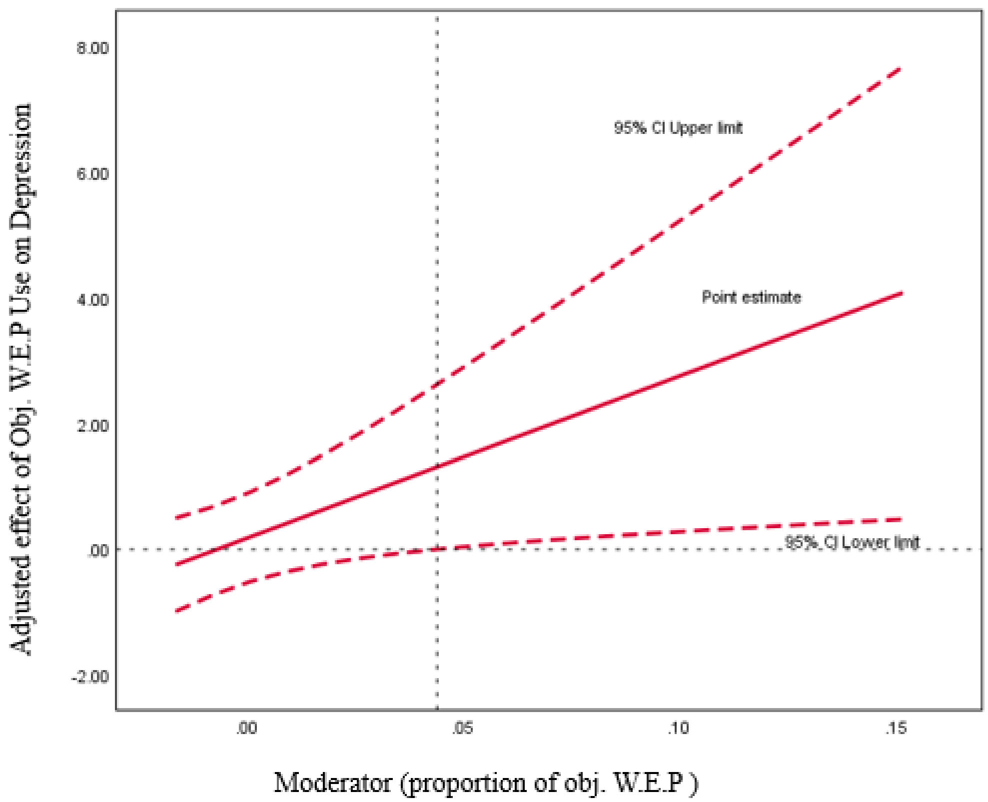

Figure 6. Johnson-Neyman values and CI's. Variables in the plot are mean centered. At the original work or educational use (W.E.P) proportion of .1481 and above (6.15% of the sample), the adjusted effect of W.E.P on depression became significant and more positive as the moderator increases. Obj. = Objective measures of use.

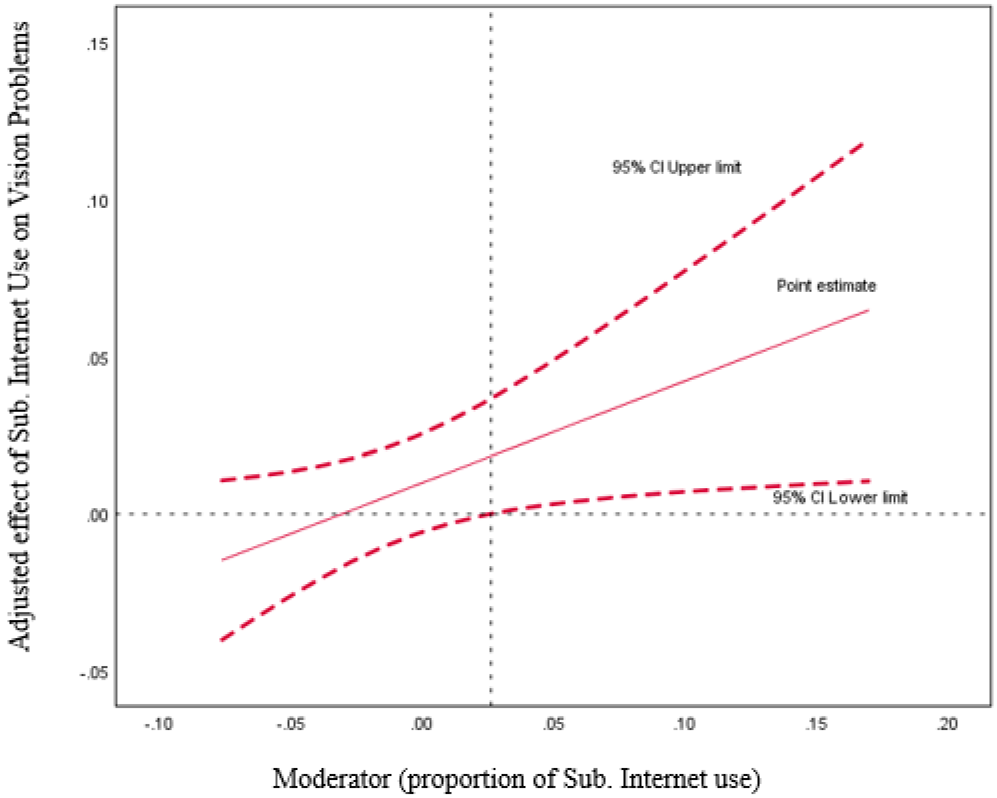

Figure 7. Johnson-Neyman values and CI's. Variables in the plot are mean centered. At the original subjective Internet use proportion of .1109 and above (26.47% of the sample), the adjusted effect of internet use on vison problems became significant and more positive as the moderator increases. Sub. = Subjective measures of use.

Appendix

Facebook Intensity Scale, modified from Ellison et al. 2007

INSTRUCTIONS: In the past week, on average, approximately how many minutes per day have you spent on each of the following social media applications *<u>on your smartphone</u>*?

Facebook

- 0 = I do not use this application
- 1 = Less than 30 minutes
- 2 = 30 - 60 minutes
- 3 = 1 - 2 hours
- 4 = 2-3 hours
- 5 = 3 - 4 hours
- 6 = 4 - 5 hours
- 7 = more than 5 hours

Instagram

- 0 = I do not use this application
- 1 = Less than 30 minutes
- 2 = 30 - 60 minutes
- 3 = 1 - 2 hours
- 4 = 2-3 hours
- 5 = 3 - 4 hours
- 6 = 4 - 5 hours
- 7 = more than 5 hours

Snapchat

- 0 = I do not use this application
- 1 = Less than 30 minutes
- 2 = 30 - 60 minutes
- 3 = 1 - 2 hours
- 4 = 2-3 hours
- 5 = 3 - 4 hours
- 6 = 4 - 5 hours
- 7 = more than 5 hours

LinkedIn

- ❍ 0 = I do not use this application
- ❍ 1 = Less than 30 minutes
- ❍ 2 = 30 - 60 minutes
- ❍ 3 = 1 - 2 hours
- ❍ 4 = 2-3 hours
- ❍ 5 = 3 - 4 hours
- ❍ 6 = 4 - 5 hours
- ❍ 7 = more than 5 hours

WhatsApp

- ❍ 0 = I do not use this application
- ❍ 1 = Less than 30 minutes
- ❍ 2 = 30 - 60 minutes
- ❍ 3 = 1 - 2 hours
- ❍ 4 = 2-3 hours
- ❍ 5 = 3 - 4 hours
- ❍ 6 = 4 - 5 hours
- ❍ 7 = more than 5 hours

Twitter

- ❍ 0 = I do not use this application
- ❍ 1 = Less than 30 minutes
- ❍ 2 = 30 - 60 minutes
- ❍ 3 = 1 - 2 hours
- ❍ 4 = 2-3 hours
- ❍ 5 = 3 - 4 hours
- ❍ 6 = 4 - 5 hours
- ❍ 7 = more than 5 hours

Yik yak

- 0 = I do not use this application
- 1 = Less than 30 minutes
- 2 = 30 - 60 minutes
- 3 = 1 - 2 hours
- 4 = 2-3 hours
- 5 = 3 - 4 hours
- 6 = 4 - 5 hours
- 7 = more than 5 hours

Tumblr

- 0 = I do not use this application
- 1 = Less than 30 minutes
- 2 = 30 - 60 minutes
- 3 = 1 - 2 hours
- 4 = 2-3 hours
- 5 = 3 - 4 hours
- 6 = 4 - 5 hours
- 7 = more than 5 hours

PokemonGo

- 0 = I do not use this application
- 1 = Less than 30 minutes
- 2 = 30 - 60 minutes
- 3 = 1 - 2 hours
- 4 = 2-3 hours
- 5 = 3 - 4 hours
- 6 = 4 - 5 hours
- 7 = more than 5 hours

Other gaming applications that allow for player-to-player interaction

- 0 = I do not use this application
- 1 = Less than 30 minutes
- 2 = 30 - 60 minutes
- 3 = 1 - 2 hours
- 4 = 2-3 hours
- 5 = 3 - 4 hours
- 6 = 4 - 5 hours
- 7 = more than 5 hours

YouTube

- 0 = I do not use this application
- 1 = Less than 30 minutes
- 2 = 30 - 60 minutes
- 3 = 1 - 2 hours
- 4 = 2-3 hours
- 5 = 3 - 4 hours
- 6 = 4 - 5 hours
- 7 = more than 5 hours

Dating Applications (e.g. Tinder)

- 0 = I do not use this application
- 1 = Less than 30 minutes
- 2 = 30 - 60 minutes
- 3 = 1 - 2 hours
- 4 = 2-3 hours
- 5 = 3 - 4 hours
- 6 = 4 - 5 hours
- 7 = more than 5 hours

Vine

- ❍ 0 = I do not use this application
- ❍ 1 = Less than 30 minutes
- ❍ 2 = 30 - 60 minutes
- ❍ 3 = 1 - 2 hours
- ❍ 4 = 2-3 hours
- ❍ 5 = 3 - 4 hours
- ❍ 6 = 4 - 5 hours
- ❍ 7 = more than 5 hours

Pinterest

- ❍ 0 = I do not use this application
- ❍ 1 = Less than 30 minutes
- ❍ 2 = 30 - 60 minutes
- ❍ 3 = 1 - 2 hours
- ❍ 4 = 2-3 hours
- ❍ 5 = 3 - 4 hours
- ❍ 6 = 4 - 5 hours
- ❍ 7 = more than 5 hours

Myspace

- ❍ 0 = I do not use this application
- ❍ 1 = Less than 30 minutes
- ❍ 2 = 30 - 60 minutes
- ❍ 3 = 1 - 2 hours
- ❍ 4 = 2-3 hours
- ❍ 5 = 3 - 4 hours
- ❍ 6 = 4 - 5 hours
- ❍ 7 = more than 5 hours

Kik

- 0 = I do not use this application
- 1 = Less than 30 minutes
- 2 = 30 - 60 minutes
- 3 = 1 - 2 hours
- 4 = 2-3 hours
- 5 = 3 - 4 hours
- 6 = 4 - 5 hours
- 7 = more than 5 hours

Reddit

- 0 = I do not use this application
- 1 = Less than 30 minutes
- 2 = 30 - 60 minutes
- 3 = 1 - 2 hours
- 4 = 2-3 hours
- 5 = 3 - 4 hours
- 6 = 4 - 5 hours
- 7 = more than 5 hours

Facebook Messenger

- 0 = I do not use this application
- 1 = Less than 30 minutes
- 2 = 30 - 60 minutes
- 3 = 1 - 2 hours
- 4 = 2-3 hours
- 5 = 3 - 4 hours
- 6 = 4 - 5 hours
- 7 = more than 5 hours

Text messaging

- ❍ 0 = I do not use this application
- ❍ 1 = Less than 30 minutes
- ❍ 2 = 30 - 60 minutes
- ❍ 3 = 1 - 2 hours
- ❍ 4 = 2-3 hours
- ❍ 5 = 3 - 4 hours
- ❍ 6 = 4 - 5 hours
- ❍ 7 = more than 5 hours

Calling

- ❍ 0 = I do not use this application
- ❍ 1 = Less than 30 minutes
- ❍ 2 = 30 - 60 minutes
- ❍ 3 = 1 - 2 hours
- ❍ 4 = 2-3 hours
- ❍ 5 = 3 - 4 hours
- ❍ 6 = 4 - 5 hours
- ❍ 7 = more than 5 hours

Other Apps that allow user-to-user communication.

- ❍ 0 = I do not use this application
- ❍ 1 = Less than 30 minutes
- ❍ 2 = 30 - 60 minutes
- ❍ 3 = 1 - 2 hours
- ❍ 4 = 2-3 hours
- ❍ 5 = 3 - 4 hours
- ❍ 6 = 4 - 5 hours
- ❍ 7 = more than 5 hours

In the past week, on average, approximately how many minutes per day have you spent using each of the following applications on your smartphone:

Web/Internet Searching on your smartphone

- 0 = I do not use this application
- 1 = Less than 30 minutes
- 2 = 30 - 60 minutes
- 3 = 1 - 2 hours
- 4 = 2-3 hours
- 5 = 3 - 4 hours
- 6 = 4 - 5 hours
- 7 = more than 5 hours

Video Streaming Apps (e.g. Netflix, HBO go, Hulu, Amazon video etc.)

- 0 = I do not use this application
- 1 = Less than 30 minutes
- 2 = 30 - 60 minutes
- 3 = 1 - 2 hours
- 4 = 2-3 hours
- 5 = 3 - 4 hours
- 6 = 4 - 5 hours
- 7 = more than 5 hours

New's Apps (e.g. BBC, CNN, FOX, NPR etc.)

- 0 = I do not use this application
- 1 = Less than 30 minutes
- 2 = 30 - 60 minutes
- 3 = 1 - 2 hours
- 4 = 2-3 hours
- 5 = 3 - 4 hours
- 6 = 4 - 5 hours
- 7 = more than 5 hours

Music Apps (e.g. Spotify, Itunes, Pandora etc.)

- 0 = I do not use this application
- 1 = Less than 30 minutes
- 2 = 30 - 60 minutes
- 3 = 1 - 2 hours
- 4 = 2-3 hours
- 5 = 3 - 4 hours
- 6 = 4 - 5 hours
- 7 = more than 5 hours

Fitness Apps (e.g. Couchto5k, Nike+, fitbit etc.)

- 0 = I do not use this application
- 1 = Less than 30 minutes
- 2 = 30 - 60 minutes
- 3 = 1 - 2 hours
- 4 = 2-3 hours
- 5 = 3 - 4 hours
- 6 = 4 - 5 hours
- 7 = more than 5 hours

Email

- 0 = I do not use this application
- 1 = Less than 30 minutes
- 2 = 30 - 60 minutes
- 3 = 1 - 2 hours
- 4 = 2-3 hours
- 5 = 3 - 4 hours
- 6 = 4 - 5 hours
- 7 = more than 5 hours

Work Apps (Word, Office, Excel, PowerPoint etc.)

- ❍ 0 = I do not use this application
- ❍ 1 = Less than 30 minutes
- ❍ 2 = 30 - 60 minutes
- ❍ 3 = 1 - 2 hours
- ❍ 4 = 2-3 hours
- ❍ 5 = 3 - 4 hours
- ❍ 6 = 4 - 5 hours
- ❍ 7 = more than 5 hours

Educational Apps (e.g. Blackboard, Kumon etc.)

- ❍ 0 = I do not use this application
- ❍ 1 = Less than 30 minutes
- ❍ 2 = 30 - 60 minutes
- ❍ 3 = 1 - 2 hours
- ❍ 4 = 2-3 hours
- ❍ 5 = 3 - 4 hours
- ❍ 6 = 4 - 5 hours
- ❍ 7 = more than 5 hours

Maps/Travel Apps

- ❍ 0 = I do not use this application
- ❍ 1 = Less than 30 minutes
- ❍ 2 = 30 - 60 minutes
- ❍ 3 = 1 - 2 hours
- ❍ 4 = 2-3 hours
- ❍ 5 = 3 - 4 hours
- ❍ 6 = 4 - 5 hours
- ❍ 7 = more than 5 hours

Shopping Apps (RetailMeNot, Amazon, Ebay etc.)

- 0 = I do not use this application
- 1 = Less than 30 minutes
- 2 = 30 - 60 minutes
- 3 = 1 - 2 hours
- 4 = 2-3 hours
- 5 = 3 - 4 hours
- 6 = 4 - 5 hours
- 7 = more than 5 hours

Food/Entertainment Apps (Fandango, Grubhub)

- 0 = I do not use this application
- 1 = Less than 30 minutes
- 2 = 30 - 60 minutes
- 3 = 1 - 2 hours
- 4 = 2-3 hours
- 5 = 3 - 4 hours
- 6 = 4 - 5 hours
- 7 = more than 5 hours

Games that do NOT allow player-to-player communication (e.g. angry birds, candy crush)

- 0 = I do not use this application
- 1 = Less than 30 minutes
- 2 = 30 - 60 minutes
- 3 = 1 - 2 hours
- 4 = 2-3 hours
- 5 = 3 - 4 hours
- 6 = 4 - 5 hours
- 7 = more than 5 hours

In the past week, on average, approximately how many minutes per day have you spent doing each activity:

Spend time by myself, without technology, relaxing or unwinding with little movement (e.g. reading for pleasure, taking a bath, knitting, meditating, etc., NOT walking or exercising)

- 0 = I do not use this application
- 1 = Less than 30 minutes
- 2 = 30 - 60 minutes
- 3 = 1 - 2 hours
- 4 = 2-3 hours
- 5 = 3 - 4 hours
- 6 = 4 - 5 hours
- 7 = more than 5 hours

Spend time by myself, without technology, participating in leisure activities (e.g. golfing, hunting, fishing, running, exercising, yoga, etc.)

- 0 = I do not use this application
- 1 = Less than 30 minutes
- 2 = 30 - 60 minutes
- 3 = 1 - 2 hours
- 4 = 2-3 hours
- 5 = 3 - 4 hours
- 6 = 4 - 5 hours
- 7 = more than 5 hours

Socializing with friends

- 0 = I do not use this application
- 1 = Less than 30 minutes
- 2 = 30 - 60 minutes
- 3 = 1 - 2 hours
- 4 = 2-3 hours
- 5 = 3 - 4 hours
- 6 = 4 - 5 hours
- 7 = more than 5 hours

Socializing with family

- 0 = I do not use this application
- 1 = Less than 30 minutes
- 2 = 30 - 60 minutes
- 3 = 1 - 2 hours
- 4 = 2-3 hours
- 5 = 3 - 4 hours
- 6 = 4 - 5 hours
- 7 = more than 5 hours

Board/Card games

- 0 = I do not use this application
- 1 = Less than 30 minutes
- 2 = 30 - 60 minutes
- 3 = 1 - 2 hours
- 4 = 2-3 hours
- 5 = 3 - 4 hours
- 6 = 4 - 5 hours
- 7 = more than 5 hours

Volunteering

- 0 = I do not use this application
- 1 = Less than 30 minutes
- 2 = 30 - 60 minutes
- 3 = 1 - 2 hours
- 4 = 2-3 hours
- 5 = 3 - 4 hours
- 6 = 4 - 5 hours
- 7 = more than 5 hours

Indicate how much you agree with the following statements.

Social Media is part of my everyday activity

- 1 = Strongly disagree
- 2 = Disagree
- 3 = Neutral
- 4 = Agree
- 5 = Strongly Agree

I am proud to tell people I am on social media

- 1 = Strongly disagree
- 2 = Disagree
- 3 = Neutral
- 4 = Agree
- 5 = Strongly Agree

Social media has become part of my daily routine

- 1 = Strongly disagree
- 2 = Disagree
- 3 = Neutral
- 4 = Agree
- 5 = Strongly Agree

I feel out of touch when I haven't logged onto my social media accounts for a while

- 1 = Strongly disagree
- 2 = Disagree
- 3 = Neutral
- 4 = Agree
- 5 = Strongly Agree

I feel I am part of a community on social media

- 1 = Strongly disagree
- 2 = Disagree
- 3 = Neutral
- 4 = Agree
- 5 = Strongly Agree

I would feel sorry if social media shut down

- ❍ 1 = Strongly disagree
- ❍ 2 = Disagree
- ❍ 3 = Neutral
- ❍ 4 = Agree
- ❍ 5 = Strongly Agree