5-7-2020

Assessing the utility of a brief abstinence test to reduce smartphone and social media use

Taylor B. Stanley

Assessing the Utility of a Brief Abstinence Test to Reduce Smartphone and Social Media Use

Taylor B. Stanley

James Madison University

A thesis submitted to the Graduate Faculty of

JAMES MADISON UNIVERSITY

In

Partial Fulfillment of the Requirements

For the degree of

Master of Arts

Psychological Sciences, Graduate Psychology

May 2020

FACULTY COMMITTEE:

Chair: Jessica G. Irons, PhD

Reader: Dr. Kethera Fogler, PhD

Reader: Dr. Bryan Saville, PhD

"Your life is what you pay attention to [sic]. If you want to spend it on video games or Twitter, that's your business. But it should be a conscious choice." – *Catherine Price*

Acknowledgements

I would like to express gratitude to my committee members Dr. Kethera Fogler and Dr. Bryan Saville for their insightful comments and continued support for helping me produce this work as well as contributing to my academic and professional development during my time at JMU. I also am very appreciative of the current members of the JMU CASHLab (Danielle Valenti, Morgan Ferretti, Shay Lumpkin, Jasmine Temple, and Maeve Register) for their help in developing and executing this product.

I would like to thank my fellow Psychological Sciences cohort members (and students in the cohort before and after mine) for their overwhelming support and camaraderie throughout our time in graduate school. I also would like to thank my parents, Cindy and David Stanley, and my brother, Bubby, for their love and unwavering support throughout my academic career.

Lastly, but certainly not least, I would like to thank my advisor, Dr. Jessica Irons, for her mentorship, encouragement, and patience during this process. I am so extremely thankful for my experiences working with you during my time at JMU and Go Team 🙌🏽.

Table of Contents

List of Tables

List of Figures

Abstract

The purpose of the current study is to investigate the efficacy of implementing a Brief Abstinence Test (BAT) for reducing smartphone and social media (SM) use among college students. A BAT is a temporally condensed version of contingency management (CM), a reinforcement-based behavioral intervention. Participants (*N* = 32, males = 6) self-reported using an iPhone updated to iOS 12 and using SM on their iPhones for at least two hours per day. Once enrolled, participants completed an online battery of health-related questionnaires and learned how to capture electronically their smartphone-use data. Participants experienced a BAT for one week, during which, researchers asked participants to reduce smartphone use by a percentage (with the majority of the reduction deriving from SM use). If participants met daily BAT contingencies, we provided online vouchers (to be exchanged for payment). Findings revealed that smartphone and SM use decreased throughout the BAT, suggesting that the BAT may be a useful experimental tool for intervening with smartphone and SM use among college students. Further work on acute and long-term clinical implications of reduced smartphone and SM use among college students is warranted.

Keywords: smartphone, social media, behavioral intervention, contingency management

Assessing the Utility of a Brief Abstinence Test to Reduce Smartphone and Social Media Use

United States consumers spend an average of five hours per day on mobile devices including smartphones, tablets, and wearable technology. Over 77% of U.S. adults own smartphones, and approximately 50% of time spent on smartphones is allocated to social media (SM), messaging, and entertainment applications (Perrin, 2018; Khalaf, 2018). Data suggest that most college students own smartphones and, among those who do, spend an average of eight hours per day (*SD* = 6) using these devices (Roberts, Yaya, & Manolis, 2014). Though smartphone use has potential benefits such as optimizing social communication and promoting development and advancement of health behavior change interventions (e.g., apps to detect opioid overdose, smoking cessation, and chronic illness management; Nandakumar et al., 2018; Blake, 2008; Fjeldsoe, Marshall, & Miller, 2009), research has demonstrated a variety of potential negative outcomes associated with excessive smartphone use, particularly among college students. Indeed, elevated smartphone use among college students is associated with health-risk behaviors such as texting while driving[1], physical inactivity, and performing poorly in academic and/or work-related domains (e.g., Cazzulino et al., 2014; Glass & Kang, 2017; Samaha & Hawi, 2016; Kim, Kim, & Jee, 2015; National Safety Council, 2019; "The 25 Scariest Texting and Driving," 2019). In addition to promoting health-risk behaviors, smartphone use has been associated with poor sleep quality, elevated stress levels, and symptoms of depression and anxiety (Elhai, Dvorak, Levine, & Hall, 2017; Oviedo-Trespalacios et al., 2019; Thomée, Härenstam, & Hagberg, M., 2011). Regardless of potential negative consequences of smartphone use, individuals use smartphones at steadily increasing rates annually (Wurmser, 2017).

Given that SM use contributes to a large proportion of overall smartphone use among college-aged individuals, it is important to consider potential consequences associated with SM use when examining smartphone use (Smith & Anderson, 2018). Indeed, past research supports that high SM use (i.e., operationalized as ≥2 hours of daily use; Sampasa-Kanyinga & Lewis, 2015) is associated with the emergence of compulsive checking, constant social comparison to peers, relationship issues, suicidal ideation, decreases in real-life social participation, reduced academic achievement, and increases in depressive symptoms (Kuss & Griffiths, 2011; Lapierre et al., 2019; Robinson et al., 2018; Oberst, Wegmann, Stodt, Brand, & Chamarro, 2017). Researchers have also observed immediate physiological and psychological consequences (akin to substance use withdrawal and craving symptoms) among participants when unable to use their smartphones. Clayton, Leshner, and Almond (2015) found that participants' heart rates, blood pressure, and subjective reports of unpleasantness increased when smartphone users were unable to answer their ringing phones. Similarly, Cheever, Rosen, Carrier, and Chavez (2014) found that individuals who were categorized as high mobile device users reported greater feelings of anxiety when their smartphones were unavailable unexpectedly. In addition, Stieger and Lewis (2018) observed that participants reported heightened craving and boredom when attempting to abstain from SM use for seven days.

Despite consistent evidence suggesting that elevated smartphone and SM use are associated with negative consequences, limited research exists examining how to modify experimentally potentially problematic (i.e., associated with negative outcomes) smartphone or SM use among college-aged individuals. There currently are no published empirical studies that attempted to intervene with smartphone use[2], and few studies that intervened with SM use. Of those data that exist, findings are mixed with respect to the impact of acute SM reduction or abstention on psychosocial outcomes. Indeed, some studies have shown that abstaining from Facebook for up to seven days increases positive affect and satisfaction with life (Hinsch &

Sheldon, 2013), decreases cortisol levels (measured via saliva samples; Vanman, Baker, & Tobin, 2018), and self-reported levels of stress (Turel, Cavagnaro, & Meshi, 2018). Other studies found no effect of acute SM abstinence with respect to affect (Stieger & Lewetz, 2018) and loneliness (Hall, Xing, Ross, & Johnson, 2019). Taken together, the majority of past studies that attempted to modify SM use experimentally measured abstention or reduction through self-report and thus may have been subject to participant self-selection biases, limiting validity of study findings (e.g., Stieger & Lewis, 2018). Additionally, most past studies did not offer incentives for reduced use (e.g., Turel et al., 2018, Stieger & Lewis, 2018; Vanman et al., 2018) with the exception of Hall et al. (2018) who offered between $25 and $50 depending on how long participants reported abstaining from SM use. Further, researchers in the aforementioned studies asked participants to abstain from various aspects of SM (e.g., Facebook only) or all SM use.

There is currently one published SM intervention study that attempted to verify behavior with means other than self-report and asked participants to reduce (rather than abstain completely) from SM use. Hunt, Marx, Lipson, and Young (2018) assigned randomly students to limit Facebook, Snapchat, and Instagram use to 30 min per day or to maintain normal app use for three weeks (verified via screenshots of iPhone Battery Life) in exchange for extra credit in a course (though no consequence occurred if the reduction criterion was not met). Findings revealed that loneliness and depressive symptoms declined in the experimental group (but not in the control group), even among individuals with lower baseline levels of depressive symptoms; however, researchers observed no differences in anxiety between control and experimental conditions throughout the procedure. Hunt and colleagues (2018) demonstrated that SM use can be manipulated experimentally and measured objectively with means other than self-report.

Given that excessive smartphone and SM use (and cessation) may lead to physiological and psychological consequences analogous to consequences of other health-risk/addictive behaviors (e.g., substance use, gambling; APA, 2013) and studies have demonstrated that abstaining from SM use may lead to improved psychosocial outcomes, it may be useful to conceptualize problematic smartphone and SM use similarly to addictive behaviors. Smartphone use, like other addictive behaviors, is likely sensitive to consequences and previous research has demonstrated that SM use is malleable (e.g., Hunt et al., 2018). As such, behavioral interventions that have been efficacious for a variety of health-risk/addictive behaviors may be viable for reducing smartphone and SM use. For example, contingency management (CM) is a reinforcement-based behavioral intervention in which individuals are offered opportunities to earn access to potential reinforcers for achieving target behavior(s). CM procedures have been effective for initiating and maintaining behavior change across a variety of health-risk behaviors, populations, and across time (Petry, Martin, Cooney, & Kranzler, 2000; Volpp et al., 2008; Rosen et al., 2007; see Sayegh, Huey, Zara, & Jhaveri, 2017 for a review). Further, CM has been shown to be efficacious for initiating and maintaining behavior change among college students in particular (e.g., smoking, Correia & Benson, 2006; physical activity, Irons, Pope, Pierce, Van Patten, & Jarvis, 2013; academic improvement, Malott & Svinicki, 1969; Van Patten, Irons, & Apple, 2015). One hallmark of CM is reliance on objective verification of behavior. Until recently, smartphone and SM use could not be verified objectively via valid means (i.e., limited to self-report[3]; Ko et al., 2015). As such, an intervention such as CM could not be effectively implemented; however, the September 2018 Apple™ iPhone iOS 12 update included a feature, ScreenTime, that allows for verification of smartphone use and specific details about application use (and does not clear/reset data when the phone is rebooted). With the iOS 12 update, CM is now a potentially viable intervention tool for reducing smartphone and SM use.

Because no previous work has tested CM for smartphone or SM use reduction, parameters of reinforcement that are minimally and/or optimally effective for inducing change have not yet been identified empirically. Given potential costs of CM[4], feasibility studies are often necessary to determine effective parameters of reinforcement to best facilitate behavior change. One model of CM that allows for initial feasibility testing is the Brief Abstinence Test (BAT). The BAT is a temporally-condensed version of CM during which researchers employ high-magnitude monetary reinforcers as a consequence for acute behavior change. Previous work suggests the BAT is a particularly effective strategy for initiating behavior change, particularly behavior that is resistant to change (e.g., Irons, Joachim, Stanley, Rininger, & Jarvis, 2019; Katz et al., 2002, Sigmon, Correia, & Stitzer, 2004; Robels et al., 2000). Additionally, the BAT is a useful experimental tool to promote initiation of behavior change in order to examine empirically physiological and psychological states that result from acute behavior change (e.g., withdrawal and craving; e.g., Robels et al., 2000).

Smartphone and SM use are inextricably associated such that reduction of one may necessarily involve reduction of the other. As such, the current study aimed to reduce both smartphone use and SM use as a composite among college students. We studied college students given that data suggests college students use smartphones and SM at higher rates compared to the general population (Lepp, Barkley, Sanders, Rebold, & Gates, 2013; Macale, 2011; Smith & Anderson, 2018). In order to test the feasibility of CM for modifying smartphone and SM use among college students, the current study implemented a BAT using parameters of reinforcement informed by previous BAT work with addictive behaviors (e.g., Irons et al., 2019). Participants in the current study were offered contingent monetary incentives to reduce smartphone and SM use (via their smartphones) over the course of one week. Given previous

BAT work, we hypothesized that the BAT would reduce smartphone and SM use among college students. Secondary aims of the current study included identifying health-related variables that may be impacted by acute phone use reduction (e.g., sleep, anxiety, physical activity, affect).

Method

Participants

Interested participants completed an online screening survey via Qualtrics (*n* = 418). Respondents who met all study criteria (*n* = 79) were invited to enroll in the study, and 32 individuals enrolled and completed the study. Participants ($N = 32$, males = 6, $n_{\text{first-years}} = 17$, $M_{\text{age}} = 19.19$, $SD_{\text{age}} = 1.09$) self-reported being at least 18 years old, maintaining SM use via their smartphones an average of two or more hours per day ($M = 4.47$, $SD = 2.08$), using an iPhone updated to iOS 12, having a Google Drive or DropBox account, and willingness to provide data as requested to verify their phone use via ScreenTime (see description below). We excluded participants who reported that their phones were “jail-broken” (i.e., modified to remove restrictions imposed by the manufacturer) or that use Apple devices other than an iPhone or MacBook (e.g., Apple Watch, iPad, etc.). See Tables 1 and 2 for sample descriptive statistics.

Materials

Self-report measures.

Demographics questionnaire. Demographics consisted of 24 questions regarding age, gender, year in school, GPA, electronic device usage, SM usage, and video game usage.

International Physical Activity Questionnaire-Short Form (IPAQ-SF). The IPAQ-SF is a seven-item measure that allows respondents to report all physical activity patterns performed in a week’s time including yard work, commuting, and recreational sport (Craig et al., 2003). In addition to the type of physical activity, participants indicate their level of work as either ‘moderate’ or ‘vigorous’. The IPAQ-SF can be used to calculate the number of minutes per week engaging in various types of exercise, as well as the number of metabolic equivalents (METs) earned for reported activity. Validity studies indicated a strong positive correlation with an activity monitor and the IPAQ data as well as provided evidence for using this instrument to accurately assess college student participation in physical activity (Dinger, Behrens, & Han, 2013).

Alcohol Timeline Follow Back Calendar (TLFB). The TLFB was used to collect self-reported alcohol use (Sobell, Brown, Leo, & Sobell, 1996). The survey appears in calendar format with room for participants to report the daily number of standard drinks in numerical form. A chart at the top of the calendar indicates what is considered a standard drink (12oz of beer, 5oz of wine, 1.5oz of hard liquor). Scores indicate the total number of standard drinks consumed in the assessed calendar period. Test-retest reliability studies indicated correlations for frequency of days drinking and maximal daily quantity over a thirty-day period (Carey, 1997).

Drinking Motives Questionnaire (DMQ). The DMQ is a 20-item questionnaire used to assess four types of motives for drinking alcohol: social, coping, enhancement, and peer pressure motives. Each item allows for a response ranging from 1 (*never*) to 6 (*almost always*). Scores can range from 5 to 30 for each drinking motive with higher scores indicating higher frequency of alcohol consumption as a result of particular motives. Instructions specify for participants to answer each question indicating how often they drink for each of the following reasons. The DMQ is valid and reliable in investigating drinking motives of young adults (Stewart, Zeitlin, & Samoluk, 1996). Internal consistency for this sample is excellent (Cronbach’s α range = .947 - .954).

Caffeine Consumption Questionnaire-Revised (CCQ-R). The CCQ-R is a valid web-based 20-item questionnaire used to gather information regarding typical caffeine consumption. Items containing caffeine are presented and participants indicate how many servings and how many days per week they consume each item. Totaled scores reflect the average amount of caffeine (in mg) an individual consumes per week. Validity data indicate that the CCQ-R is a valid approach for operationalizing self-reported caffeine use (Irons et al., 2016).

Pittsburgh Sleep Quality Index (PSQI). The PSQI is a 19-item questionnaire that provides indices of sleep patterns (i.e., quality, latency, duration, medication use, disturbance, daytime dysfunction) through a one-month interval of time. Sleep pattern indices can be calculated separately or summed to provide a global sleep quality score. Global scores can range from 0 to 21 with higher scores indicating worse sleep quality. Participants answer open-ended questions that are scored based on established categories and questions on a 4-point Likert-scale (0 = *very good* to 3 = *very bad*; Buysse, Reynolds, Monk, Berman, & Kupfer, 1989). The PSQI is a psychometrically sound measure to use across a variety of clinical and non-clinical populations (Carpenter & Andrykowski, 1998).

State Trait Anxiety Index (STAI). The STAI is a two-part 40-item measure used to assess trait and state anxiety (Spielberger, Gorsuch, Lushene, Vagg, & Jacobs, 1983). All items are rated on a Likert-type scale from 1 (*almost never*) to 4 (*almost always*). State and trait subscores can range from 20 to 80 with higher scores indicating higher levels of state/trait anxiety. The STAI has demonstrated consistently appropriate reliability and validity with an undergraduate population (Metzger, 1976). Internal consistency for this sample is excellent (Cronbach’s α range = .95- .96).

Positive and Negative Affect Scale (PANAS). The PANAS consists of two 10-item scales, one measuring positive affect and the other negative affect, on which participants are asked to indicate to what extent they feel the emotion at the current moment. Participants indicate responses using a 5-point Likert scale (1 = *very slightly or not at all* to 5 = *extremely*). Scores for both scales can range from 10 to 50 with higher scores reflecting higher levels of positive/negative affect. The PANAS is a reliable and valid scale that is also brief and easy to administer (Watson, Clark, & Tellegen, 1988). Internal consistency for this sample is good (Cronbach's α range = .85 - .88).

Smartphone Addiction Scale – Short Version (SAS-SV). The SAS-SV consists of ten items on which participants indicate the extent they agree or disagree with statements about their smartphone usage. Participants indicate responses using a 6-point Likert scale (1 = *strongly disagree* to 6 = *strongly agree*). SAS-SV scores can range from 10 to 60 with higher scores indicating greater smartphone addiction. The SAS-SV is a reliable and valid scale and has been administered in previous smartphone studies (e.g., Samaha & Hawi, 2016). Internal consistency for this sample is good (Cronbach's α range = .88 - .93).

Social Media Addiction Severity Index (SMASI). The SMASI is an 18-item modified version of the Bergan Facebook Addiction Scale (BFAS; Andreassen et al., 2012). Researchers substituted "social media" for the word "Facebook" in all items to capture all forms of SM use rather than just Facebook use. The SMASI has not yet been validated; however, the BFAS is a reliable and well-validated measure that has been used to capture six constructs of addictive behavior in college students (salience, conflict, mood modification, withdrawal, tolerance, and relapse). Participants indicate responses using a 5-point Likert scale (1 = *very rarely* to 5 = *very* *often*). Scores can range from 18 to 90 with higher scores indicating greater SM addiction. Internal consistency for this sample is excellent (Cronbach's α range = .92 - .93).

Phone-use measure.

Apple ScreenTime. ScreenTime is a feature that was incorporated in the September 2018 Apple iOS 12 software update that informs users how much time is used on specific apps and websites. ScreenTime includes a detailed report about how a smartphone device is used, listing specifically the apps a user has visited and for how long, the number of notifications a user receives in a day, the number of times a user has picked up their phone (Apple defines a "pickup" users pick up *and* unlock their phones). ScreenTime is accessible at any time (and operates unless the user manually turns off the feature or the phone is turned off). ScreenTime provides daily phone use data and also creates a chart detailing weekly usage and provides weekly averages for phone and specific app use. ScreenTime also breaks down the apps using established categories from the App Store (e.g., Social Networking, Productivity, Games, etc.) to provide users with information regarding how they are interacting with their iPhone. References to SM use in the Method, Data Analysis Plan, and Results sections are exclusively SM use via smartphone.

Procedure

Intake. Interested participants completed an online screening survey to determine eligibility (see criteria above and Table 3 for screener descriptive statistics). The screening survey did not reveal the nature of its intended use and included questions and measures unrelated to smartphone and SM use in effort to reduce bias or sets. After reviewing screening survey responses, we invited qualified participants via email to enroll in the study. After agreeing to enroll in the study, participants completed an online intake survey that included informed consent and a battery of health-related questionnaires (see Materials above). Participants also used ScreenTime to indicate how much time they spent on their smartphone and used SM for the seven days prior to intake survey completion and for the day of intake survey completion. Participants captured ScreenTime reports by completing a screen recording of their data and uploading the recording to Google Drive or DropBox (see Appendix A for instructions we provided participants for ScreenTime data extraction). We used intake ScreenTime data to calculate average daily smartphone and SM use as baseline criterion for the BAT. Participants received a $5.00 voucher for completing the intake survey. After participants completed the intake survey, we emailed participants with instructions for when to start the BAT and provided participants with baseline smartphone and SM use data.

BAT. Starting the Monday after intake survey completion, participants experienced a BAT for seven days. During the BAT, participants received daily monetary compensation in the form of online vouchers (that could be exchanged for cash at any time upon request) uploaded to their Google Drive or DropBox folders for meeting specified smartphone and SM reduction contingencies. For example, on Day 1, we asked participants to reduce overall smartphone use by 30% compared to baseline use; two-thirds of that reduction needed to be a reduction in SM use. SM use was defined during the BAT as any of the apps grouped under “Social Networking” (e.g., iMessage, Facebook, Instagram, Snapchat, etc.) in iOS 12 Screen Time. Applications that are categorized under Apple’s preset groups such as “Productivity” (e.g., e-mail applications) and “Entertainment” (e.g., Spotify, YouTube) did not count towards SM estimates. If participants met the contingencies, they received $10.00 vouchers. Additionally, for each day of the BAT that participants uploaded their phone-use data to Google Drive or DropBox (regardless of whether they met BAT contingencies) they received $1.50 (see Table 4). On Day 7 of the

BAT, participants completed an online survey that included the same battery of health questionnaires as the intake session.

Follow-up. We provided participants a link to an online survey three weeks following the BAT that included a battery of health-related questionnaires, open-ended questions for participants to describe their experiences throughout the study, and a question for participants to provide current phone and SM use data from ScreenTime. Participants could have earned up to $93.75 throughout the study if all contingencies were met (and $25.50 if only data upload contingencies were met). Additionally, participants completed researcher-developed items about smartphone and SM use before starting and after completing the BAT and answered questions regarding the intervention.

Data Analysis Plan

Researchers analyzed data using SPSS (Version 26.0). Analyses consisted of descriptive statistics, primary outcome analyses, and exploratory analyses. All correlations reported are Pearson's Product Moment correlation coefficients. We counted missing ScreenTime data during the BAT as not having met BAT criteria for that day. Researchers obtained means and standard deviations for daily (12am - 11:59pm) and total (throughout the BAT) smartphone and SM use in minutes (via ScreenTime) and all health-related variables to describe adequately sample characteristics. Researchers conducted internal consistency analyses for all appropriate measures. All internal consistency data are presented as ranges to reflect internal consistency across all three time points at which we administered measures. Within-subjects comparisons were used to examine smartphone and SM use percent-change mean differences and potential changes in health outcome variables. Within-subject comparisons were conducted for cases that included complete data for all time points. Planned contrasts for within-subject comparisons of data derived from Days 4-7 of the intervention are averaged given that BAT criteria is the same for each of these days. A series of exploratory multiple regression analyses were conducted to determine if health-related variables predict smartphone and SM use and whether they predict uniquely responsiveness to a BAT paradigm.

We expressed differences between baseline smartphone and SM use and reported smartphone and SM use during each day of the BAT as a percentage. We converted smartphone and SM use (from min) to a percentage of baseline use by taking the reported smartphone and SM use for each day and dividing by participants' baseline smartphone and SM use. We then subtracted the new percentage by 100 to obtain the reduction percentage at each day of the BAT compared to baseline for each participant. For example, if a participant had a baseline smartphone use of 200 min, and reduced overall smartphone use to 120 min on Day 1 of the BAT, the participant used 60% of their baseline use on Day 1 (120min/200min) x 100 = 60%, and reduced overall smartphone use by 40% (100 – 60 = 40%) on Day 1 of the BAT.

Results

Screener Data

We conducted analyses on all individuals who completed the online screening survey (N = 418; See Appendix B and Table 5 for results).

Primary Analyses

Smartphone and SM use during the BAT.

We computed average baseline smartphone use (M = 331.50, SD = 131.78) and SM use in min (M =147.16, SD = 77.00) using ScreenTime. We also obtained descriptive statistics for smartphone and SM use (in min) for each day during the BAT (see Tables 6 and 7). Twenty-three participants provided smartphone and SM data for all seven days of the BAT. Six of 32 participants met BAT criteria for all seven days; 16 participants met BAT criteria for at least four of the seven days (see Figure 1).

A repeated-measures ANOVA (Greenhouse-Geisser adjusted) revealed reduced smartphone use percentages during the BAT compared to baseline, $F(3.68) = 28.58$, $p < .001$, $\eta_p^2 = .55$, observed power = 1.00. On average, participants reduced smartphone use by 49.19% ($p < .001$, $SE = 5.36$, CI 95% [38.11, 60.26]) compared to baseline on Day 1 of the BAT, by 52.23% ($p < .001$, $SE = 5.16$, CI 95% [41.55, 62.91]) compared to baseline on Day 2 of the BAT, by 59.64% ($p < .001$, $SE = 4.83$, CI 95% [49.65, 69.62]) compared to baseline on Day 3 of the BAT, and by 46.81% ($p < .001$, $SE = 6.65$, CI 95% [26.33, 61.26]) compared to baseline and on Days 4 – 7 of the BAT, see Figure 2.

A repeated-measures ANOVA (Greenhouse-Geisser adjusted) revealed reduced SM use percentages during the BAT compared to baseline, $F(4.44) = 11.36$, $p < .001$, $\eta_p^2 = .35$, observed power = 1.00. On average, participants reduced SM use by 51.17% ($p = .001$, $SE = 9.30$, CI 95% [17.91, 84.42]) compared to baseline on Day 1 of the BAT, by 55.03% ($p < .001$, $SE = 7.75$, CI 95% [27.33, 82.74]) compared to baseline on Day 2 of the BAT , by 63.65% ($p < .001$, $SE = 4.09$, CI 95% [49.02, 78.27]) compared to baseline, on Day 3 of the BAT and by 51.32% ($p < .001$, $SE = 8.35$, CI 95% [14.31, 81.72]) compared to baseline on Days 4 – 6 of the BAT . Participants, on average, reduced SM use by 31.49% ($p < .001$, $SE = 10.63$, CI 95% [-6.53, 69.51]) compared to baseline on Day 7 of the BAT, see Figure 3.

A repeated-measures ANOVA revealed changes in smartphone use (in min) between baseline ($M = 303.18$, $SD = 133.98$), day 7 of the BAT ($M = 172.00$, $SD = 119.17$), and three-weeks post-BAT ($M = 294.18$, $SD = 96.70$), $F(2) = 7.84$, $p = .002$, $\eta_p^2 = .33$, observed power = .93. On average, participants reduced smartphone use from Baseline to Day 7 of the BAT by

131.18 min (p = .009, SE = 37.57, CI 95% [30.74, 231.61]), and increased smartphone use by 122.18 min (p = .018, SE = 38.71, CI 95% [-225.66, -18.70]) from Day 7 of the BAT to three-weeks post-BAT. Smartphone use, on average, did not differ between baseline and three-weeks post-BAT, see Figure 4.

A repeated-measures ANOVA revealed small changes in SM use (in min) between baseline (M = 134.60, SD = 102.92), day 7 of the BAT (M = 102.92, SD = 141.47), and three-weeks post-BAT (M = 141.47, SD = 69.09), $F(2) = 1.52$, p = .235, η_p^2 = .09, observed power = .30. On average, participants reduced SM use by 31.68 min (p = .644, SE = 24.37, CI 95% [-34.54, 97.90]) from Baseline to Day 7 of the BAT, and increased SM use by 38.55 min (p = .341, SE = 22.85, CI 95 % [-100.64, 23.54]) from Day 7 of the BAT to three-weeks post-BAT. SM use, on average, did not differ between baseline and three-weeks post-BAT, see Figure 5.

Health outcomes during the BAT.

We conducted a series of repeated-measures ANOVAs to examine potential changes in health-related outcomes from baseline, one day post-BAT, and three-weeks post BAT for participants who provided these data for all three time points (n = 21).

A repeated-measures ANOVA revealed changes in SMASI total scores between intake (M = 45.71, SD = 12.55), post-BAT (M = 41.00, SD = 13.07), and three-week post-BAT (M = 40.52, SD = 11.96), $F(2) = 5.23$, p = .010, η_p^2 = .21, observed power = .80. On average, SMASI total scores reduced by 4.71 points (p = .045, SE = 1.77, CI 95% [0.08, 9.35]) from intake to post-BAT.

A repeated-measures ANOVA revealed change in salience subscores of the SMASI between intake (M = 8.43, SD = 2.01), post-BAT (M = 7.14, SD = 2.73), and three-week post-BAT (M = 6.95, SD = 2.33), $F(2) = 5.87$, p = .006, η_p^2 = .23, observed power = .85. On average, salience subscores decreased by 1.48 points (*p* = .017, *SE* = 0.48, CI 95% [0.23, 2.72]) from intake to three-weeks post-BAT.

A repeated-measures ANOVA (Greenhouse-Geisser adjusted) revealed change in mood modification subscores of the SMASI between intake (*M* = 7.90, *SD* = 3.19), post-BAT (*M* = 7.00, *SD* = 3.39), and three-week post-BAT (*M* = 6.48, *SD* = 3.37), *F*(1.51) = 5.10, *p* = .019, η_p^2 = .20, observed power = .70. On average, mood modification subscores decreased by 1.42 points (*p* = .056, *SE* = 0.56, CI 95% [-0.03, 2.89]) from intake to three-weeks post-BAT.

A repeated-measures ANOVA revealed change in smartphone addiction (SAS-SV) scores between intake (*M* = 34.14, *SD* = 11.81), post-BAT (*M* = 29.57, *SD* = 12.34), and three-week post-BAT (*M* = 30.95, *SD* = 10.65), *F*(2) = 3.15, *p* = .054, η_p^2 = .14, observed power = .57. On average, SAS-SV scores decreased by 4.57 points (*p* = .061, *SE* = 1.82, CI 95% [-0.17, 9.31]) from intake to post-BAT.

A repeated-measures ANOVA revealed change in drinking for social motives scores between intake (*M* = 14.00, *SD* = 5.97), post-BAT (*M* = 12.81, *SD* = 5.96), and three-week post-BAT (*M* = 13.33, *SD* = 5.30), *F*(2) = 2.05, *p* = .142, η_p^2 = .09, observed power = .40. On average, drinking for social motives decreased by 1.19 points (*p* = .226, *SE* = 0.64, CI 95% [-0.47, 2.85]) from intake to post-BAT, and increased by 0.52 points (*p* = 1.00, *SE* = 0.60, CI 95% [-2.85, 1.03]) from post-BAT to three-weeks post-BAT.

A repeated-measures ANOVA (Greenhouse-Geisser adjusted) revealed change in the number of minutes participants reported engaging in vigorous physical activity (PA) between intake (*M* = 137.67, *SD* = 153.91), post-BAT (*M* = 79.67, *SD* = 47.83), and three-week post-BAT (*M* = 67.67, *SD* = 33.11), *F*(1.15) = 2.98, *p* = .099, η_p^2 = .18, observed power = .39. On average, the amount of time spent engaging in vigorous PA decreased by 58.00 minutes (*p* =

.416, *SE* = 36.94, CI 95% [-42.40, 158.40]) from intake to post-BAT, and decreased by an additional 12.00 minutes (*p* = .960, *SE* = 11.64, CI 95% [-19.63, 43.63]) from post-BAT to three-weeks post-BAT.

A repeated-measures ANOVA revealed change in weekly caffeine consumption (in mg) between intake (*M* = 931.95, *SD* = 878.77), post-BAT (*M* = 1,037.41, *SD* = 1530.95), and three-week post-BAT (*M* = 702.68, *SD* = 975.94), *F*(2) = 2.02, *p* = .146, η_p^2 = .09, observed power = .39. On average, caffeine consumption increased by 105.47mg (*SE* = 208.49, CI 95% [-650.17, 439.24]) from intake to post-BAT, and decreased by 334.73mg (*SE* = 147.85, CI 95% [-51.55, 721.01]) from post-BAT to three-weeks post-BAT.

A repeated-measures ANOVA revealed change in the number of standard drinks participants consumed in the past week between intake (*M* = 5.10, *SD* = 5.97), post-BAT (*M* = 5.33, *SD* = 6.66), and three-week post-BAT (*M* = 2.48, *SD* = 3.74), *F*(2) = 2.80, *p* = .073, η_p^2 = .12, observed power = .52. On average, reported standard drink consumption did not change from intake to post-BAT (*p* = 1.00, *SE* = 1.25, CI 95% [-3.51, 3.03] but decreased by 2.86 standard drinks (*p* = .228, *SE* = 1.53, CI 95% [-1.13, 6.85]) from post-BAT to three-weeks post-BAT.

Exploratory Analyses

Health-related correlates of smartphone and SM use.

Researchers examined the relations between baseline smartphone, baseline SM use, and self-reported SM use with health-related variables. Findings revealed no relation between self-reported SM use and baseline SM use (determined via ScreenTime; *r* = .18, *p* = .330). Results also revealed a negative relation between baseline smartphone use and GPA, *r* = -.38, *p* = .032;

however, smartphone and SM use did not relate to any other health-related variables (see Table 8).

ScreenTime correlates of smartphone and SM use.

Throughout the BAT, we observed a generally positive relation between smartphone and SM use, between the number of notifications participants received and the number of times participants picked up their smartphones, between smartphone use and the number of times participants picked up their phones, between SM use and the number of times participants picked up their smartphones, between smartphone use and the number of notifications participants received, and between SM use and the number of notifications participants received (see Table 9).

Predictors of BAT efficacy.

We conducted a series of exploratory multiple regression analyses to determine if any health-related variables predicted the number of days participants met BAT criteria. We first examined the relations between the number of days participants met BAT criteria and all health-related variables. Findings revealed that state anxiety (r = -.27), negative affect (r = -.22), GPA (r = .39), relapse subscores of the SMASI (r = -.24), and DMQ – enhance subscores (r = .29) related most strongly with the number of days participants met BAT criteria. Given these findings, we constructed a series of hierarchal regression models to examine whether these variables predict BAT efficacy uniquely and/or as a set. Findings revealed that a model with all five predictors explains 29.4% of the variance in the number of days participants met BAT criteria, $F(5, 24) = 2.00$, $p = .116$, $R^2 = .29$; however, the only predictors in this model that explained a meaningful amount of variance above and beyond the other predictors were GPA (b = 1.23, sr^2 = .10), DMQ-enhance (b = 0.17, sr^2 = .13), and relapse subscores of the SMASI (b = -

0.30, sr^2 = .09). Therefore, researchers constructed a second hierarchical regression model with only GPA, DMQ-enhance, and relapse subscores of the SMASI. The overall model explains 32.3% of the variance in the number of days participants met BAT criteria, $F(3, 28) = 4.45$, p = .011, R^2 = .32, with all three predictors contributing uniquely to the model. Specifically, for every unit increase in SMASI-relapse scores and GPA, predicted BAT efficacy is expected to increase (b_{GPA} = 1.21, $b_{DMQenhance}$ = 0.18; while holding other predictors constant), while for every unit increase in DMQ-enhance scores, predicted BAT efficacy is expected to decrease (b = -0.33) when holding other predictors in the model constant; see Table 10 for regression coefficients for all predictors in both models and overall efficacy of the models in predicting the number of days participants met BAT criteria).

We also conducted a series of exploratory multiple regression analyses to examine if any health-related variables predicted smartphone and SM use percent change throughout the BAT. First, researchers examined the relations between Day 7 smartphone use (expressed as a percentage of baseline use) with health-related outcomes. Variables that related most strongly to Day 7 smartphone use were smartphone addiction scores (r = .13), DMQ-enhance scores (r = .17), negative affect (r = -.18), and state anxiety (r = -.17). A single-predictor entry regression model with all four variables included in the model explained 9.4% of the variability in smartphone use change throughout the BAT, $F(2, 24) = 0.62$, p = .652, R^2 = .09, with DMQ-enhance scores explaining the most variance above and beyond the other predictors in the model (p = .306, b = 1.56, CI 95 % [-1.52, 4.65], sr^2 = .04). See Table 11 for regression coefficients and other statistical information for all predictors.

Researchers repeated this process for SM use change throughout the BAT. Variables that related most strongly to Day 7 SM use were GPA (r = .38), DMQ-social scores (r = .36), DMQ-enhance scores (r = .36), overall sleep quality (r = -.25), and smartphone addiction total scores (r = .28). We constructed a hierarchical multiple regression model with all five variables and, as a set, those five predictors explained 32.2% of the variance in SM use change throughout the BAT, $F(5, 22) = 2.093$, $p = .105$, $R^2 = .32$. No single predictor contributed meaningfully to the model while holding all other variables constant (see Table 12 for regression coefficients and other statistical information for each predictor).

Follow-up outcomes.

Of the participants who responded to the follow-up questions on the three-week post-BAT survey (n = 24), almost half (n = 11) endorsed that they had thought about trying to or have tried reducing their smartphone and SM use prior to participating in the study. Additionally, nearly half of participants (n = 11) reported that it was "moderately difficult" to reduce smartphone and SM use throughout the intervention (response options ranged from "*Extremely easy*" to "*Extremely difficult*"). Further, 18 participants reported that their smartphone and SM use had changed since completing the BAT. Specifically, 12 participants reported that their smartphone and/or SM use had decreased since completing the study. When asked about how participants attempted to modify their smartphone and SM usage during the intervention, four participants reported engaging in non-phone-related activities (e.g., studying, exercising), four participants reported modifying phone settings to try to reduce their use (e.g., turning off notifications, deleting social media applications, putting their phones on "Do Not Disturb"), and two participants reported that they abstained from using their phones while in classes and/or kept their phone hidden during the school day. Lastly, we asked participants to indicate how much money would they need to be paid to repeat the same intervention. Seventeen participants reported that they would complete the intervention again for the same incentive amount

($10.00/day; these participants, on average, met BAT criteria 4.35 days (*SD* = 2.47), while four participants indicated that they would complete the intervention again for $15.00/day (these participants, on average, met BAT criteria 2.75 days (*SD* = 2.87).

Discussion

The current study examined the feasibility of implementing a seven-day BAT for reducing smartphone and SM use among college students who self-reported using SM (via their smartphones) for at least two hours per day. Results revealed that, on average, smartphone and SM use decreased each day of the BAT relative to baseline use, suggesting that smartphone and SM use can be manipulated experimentally, and the BAT may be a useful experimental tool for intervening with smartphone and SM use. Given these findings, it seems that participants may have been attempting to reduce smartphone and SM use throughout the BAT; however, the majority of participants were not reducing smartphone and/or SM use enough to meet specified BAT criteria (and gain access to potential monetary reinforcers). Specifically, only six participants met BAT criteria for all seven days of the BAT, and only half of participants met BAT criteria for at least four days of the BAT. We offer potential explanations for primary study findings.

It is possible that participants did not meet BAT criteria because parameters of reinforcement in this study (e.g., reduction criteria, incentive magnitude, reinforcer delay) were functionally arbitrary with respect to target behaviors. Given that the current study is the first to examine the utility of CM for reducing smartphone and SM use, there are no currently known best practices for implementing CM for these behaviors. As such, researchers informed parameters of reinforcement for the current study based on past research demonstrating CM efficacy of modifying other health-risk behaviors among college students (Irons & Correia, 2008; Irons et al., 2019). For example, we implemented percent reduction (compared to baseline) criteria in effort to individualize the intervention (e.g., Romanowich & Lamb, 2014). In contrast, Hall and colleagues (2019) asked all participants to abstain completely from SM and Hunt and colleagues (2018) asked all participants to reduce to 30 min of SM use. We also implemented a relatively large magnitude (overall) potential reinforcer for a brief period of time as is typical with BAT studies; however, magnitude of potential reinforcers must match the abuse liability of the behavior and, given lack of data, we chose a reinforcer value between cocaine (Robles et al., 2000; $100) and nicotine (Irons & Correia, 2008; $65). Additionally, prior to data collection, we asked college students to estimate informally how much money they would need to be paid to reduce smartphone use by 50% and the majority of respondents reported they would accept $10.00. In addition, we made access to monetary incentives immediate upon earning; participants could withdraw funds electronically upon request or come pick up cash the day of request (Correia & Little, 2006; Benson, Little, Henslee, & Correia, 2009). Though most participants did not meet all contingencies, the majority of participants did reduce use suggesting that the BAT was efficacious. Future research should consider details of the current study as well as past CM studies (BAT and otherwise) when developing smartphone and/or SM contingencies. Research might also consider determining relative abuse liability of smartphone use and SM use in effort to inform systematically reinforcer parameter decisions for interventions.

Given findings of the current study, it is likely that smartphone and SM use likely differs from other health-risk behaviors with respect to some parameters of reinforcement. Specifically, smartphone and SM use likely compete with fewer potentially reinforcing behaviors relative to other health-risk behaviors. For example, most individuals can engage in smartphone and SM use nearly continuously throughout the day without experiencing or perceiving impairments in functioning (e.g., substance effects) or losing access to other potential reinforcers (e.g., choosing whether to engage in substance use or go to class sober). Smartphone and SM use may also complement potentially reinforcing behaviors differently than other health-risk behaviors. For instance, smartphone and SM use may promote reinforcer value of social gatherings because of the ability to incorporate individuals not in attendance (e.g., via video messaging) as well as the ability to document and share the experience formally. While individuals sometimes engage in other health-risk behaviors in attempt to improve social gatherings (e.g., substance use), individuals may lose access to more potential reinforcers compared to engaging in smartphone and SM use (e.g., if someone engages in substance use at a social gathering, they may lose their ability to drive themselves home but engaging in smartphone and SM use are less likely to yield such consequences).

Additionally, most health-risk behaviors occur under limited conditions (e.g., times, locations, etc.) and do not occur in contexts in which negative consequences are likely to occur as a result of use. For example, individuals may not consume alcohol while at class/work given the potential for impairment and/or social or legal repercussions but may check their smartphones or use SM throughout the school or work day with little to no consequence. Further, serious negative consequences resulting from elevated smartphone and SM use (e.g., car accident as a result of texting while driving) may occur on different schedules of punishment compared to serious negative consequences of other health-risk/addictive behaviors (e.g., job loss). For instance, individuals may engage in smartphone use while driving every time they operate a vehicle but may not ever experience an accident related to their use. Conversely, one instance of a failed drug test may warrant employment termination.

Previous laboratory studies have demonstrated that behavior change may reinforce subsequent behavior change (i.e., once participants make initial contact with potential reinforcers associated with change, the behavior will likely re-occur; Higgins, Badger, & Budney, 2000; Hiel et al., 2004). Though nearly half of participants who completed the three-week follow-up survey reported having *thought* about modifying smartphone and SM use prior to study onset we did not collect data on how many attempts were made and for what duration and/or for what reason(s). Future smartphone and SM use intervention studies may benefit from characterizing smartphone and/or SM use change attempts that occur prior to intervention in effort to examine if BAT responsiveness differs as a function of previous attempts.

Study findings support that change in smartphone and SM use can likely be accounted for by experimental contingencies set in the study. Specifically, participants, on average, reduced smartphone and SM use relative to baseline during the BAT but behavior showed a trend towards baseline at follow-up assessment. While this pattern is ideal from an experimental standpoint (as we are able to draw causal conclusions that BAT contingencies were affecting smartphone and SM use), further work on the clinical utility of CM for smartphone and SM use is warranted. Future research should examine whether behavior change that occurs under CM contingencies will be maintained over time once contingencies have been removed and, if so, under what conditions that change is most likely to be sustained.

Current study findings contrast previous study findings that self-reported SM use relates strongly with negative consequences (e.g., anxiety, Oberst et al., 2017; social media addiction, Robinson et al., 2018) such that the current study observed weak (or no) relations between self-reported SM use and health-related outcomes; however, there are methodological differences between the current study and past studies that may explain why we failed to replicate strong relations. Specifically, Oberst et al. (2017) examined relations between social networking use and mental health outcomes (i.e., anxiety and depressive symptoms) among an adolescent South-American sample. Oberst et al. (2017) note in their literature review that severity of consequences associated with Internet use may be culturally or geographically-dependent. For example, Asian countries (particularly, China, Singapore, and South Korea) deemed problematic Internet use a serious public health concern and passed legislation to restrict adolescent access to Internet cafés in attempt to reduce problematic Internet use (though prior to Oberst's study no data had been collected on the impact of Internet use in South American countries; Li, Newman, Li, & Zhang, 2016). To the extent that SM use is analogous to Internet use, cultural or geographical differences in SM use (or perceptions of SM use) could be a potential explanation for current study failure to replicate strong relations between SM use and health-related outcomes. In past research that sampled American college students (e.g., Robinson et al., 2018), researchers examined specific aspects of SM use (e.g., comparison to peers through SM, being tagged in 'unflattering pictures' on SM) rather than SM use generally, which may also contribute to the current study's failure to replicate strong relations between SM use and negative outcomes.

It may also be possible that the study sample may not actually experience any negative consequences as a result of their smartphone and/or SM use; however, we attempted to recruit a sample that are deemed "at risk" for experiencing negative consequences as a result of their elevated self-reported use (Sampasa-Kanyinga & Lewis, 2015). Lastly, the current study examined relations between SM use and exploratory health-related outcomes (e.g., drinking motives, caffeine use) while previous work did not collect such data. Further work is needed to clarify variables that are related to SM use and under what conditions.

Current study findings also failed to replicate past research that found strong relations between smartphone use and negative health outcomes (e.g., Elhai et al., 2017; Oviedo-Trespalacios et al., 2019; Thomée et al., 2011); however, the current study did not collect self-report smartphone use data in the screening survey (and only baseline data from ScreenTime from participants who completed the BAT). Therefore, it may be possible that failure to replicate such strong relations may result from recruiting a sample using several inclusion criteria (which may have limited variability in participant responses with respect to measured outcomes) and by collecting phone use data from ScreenTime. Past studies derived data from large samples (N > 1000), implemented few/no exclusion criteria, and primarily used self-report methods of mobile/smartphone use. Future work may examine relations between negative outcomes and smartphone use with methods other than self-report now that such technology exists.

It may also be possible that time spent using smartphones does not directly lead to negative consequences, but rather *how* users interact with their smartphones. For example, individuals may spend elevated amounts of time using smartphones; however, they may be using smartphones for activities unrelated to SM (e.g., tracking physical activity, managing school/work-related tasks, etc.). In fact, Przybylski et al. (2019) examined the impact of digital screen engagement among children ranging from six months to 17 years old found that moderate amounts of screen time (defined in the study as 1-2 hours of overall screen time exposure per day) were related to slightly higher levels of psychosocial functioning (i.e., social and emotional functioning rated by a caregiver) compared to lower or higher levels of use. Because ScreenTime allows individuals to view how they are interacting specifically with their iPhones (i.e., listing daily and weekly time spent using specific applications), future studies may benefit from examining how users are allocating time using smartphones. Indeed, follow-up findings revealed that some participants attempted to reduce usage by engaging in non-phone use behaviors (e.g., exercise, completing schoolwork). Therefore, future CM work might consider intervening with smartphone use by not only asking participants to reduce overall SM use, but also promote usage of health-promoting applications and/or incentivize engaging in non- smartphone/SM use activities. Indeed, past studies have indicated an inverse relation between substance-free reinforcement and substance use, suggesting that attempting to increase participation of substance-free alternatives may more effectively promote long-term reduction and/or abstinence (see Acuff, Dennhardt, Correia, & Murphy, 2019 for a review).

Additionally, findings from the current study revealed generally strong positive relations between smartphone and SM use and the number of notifications participants received and the number of times participants picked up their phone during the BAT. These data suggest that individuals may be able to self-monitor smartphone and SM use by modifying notification settings (e.g., using “Do Not Disturb” functions) and/or limiting the number of times they pick up their smartphones in effort to reduce usage. Future work could examine experimentally whether modifying notification settings impacts directly smartphone and SM use.

Although there are a number of strengths of the current study (e.g., verifying behavior objectively, potential ecological validity by using online data-collection, incentivizing daily data submission uploads during the BAT and follow-up survey completion to minimize participant attrition), limitations should be considered. First, researchers established baseline smartphone and SM use with ScreenTime data from a single week before individuals completed intake. It is possible that participants’ smartphone and SM usage during baseline was not representative of their typical use and thus the BAT contingencies could have been, unintentionally, more or less demanding. For example, if a participant’s baseline data reflect unusually high smartphone and/or SM use, then the BAT contingencies would be less challenging to meet if typical use more closely approximates the contingencies. Likewise, if a participant's baseline data reflect unusually low smartphone and/or SM use, BAT contingencies may be more challenging given that typical use is elevated relative to baseline. Future work may collect baseline use for longer than one week to establish baseline use more accurately.

Second, we exclusively recruited iPhone users for the current study because other smartphone developers did not have a ScreenTime equivalent at the time of data collection; however, iPhone users make up ~45% of all smartphone users (Holst, 2019). Once technology similar to ScreenTime is available on non-iPhone devices, future research may include non-iPhone users to study a more representative sample of all smartphone users. We piloted the efficacy of using a third-party application to verify smartphone and SM use time in addition to ScreenTime and results yielded large differences in time spent using smartphones and SM between ScreenTime and the third-party application, therefore, we decided to only use ScreenTime and recruit only Apple iPhone users.

Lastly, we excluded individuals who reported having Apple devices other than iPhones and MacBooks in order to minimize the possibility of participants engaging in SM and smartphone-like application use with other devices (e.g., Apple Watch, iPad) during the study; however, it is possible that participants may have engaged in SM use using a computer or non-Apple device that we did not account for in the screening survey. We also excluded these participants because at the time of data collection, usage data from all Apple devices that used the same iCloud account (not just iPhone usage) counted towards ScreenTime estimates. Since data collection, Apple released an update that allows for ScreenTime to function on an Apple computer and that allows users to determine if they would like non-iPhone usage data (e.g., Apple Watch, iPad) to count towards ScreenTime estimates. Future work might examine SM use from an iPhone and computer to more accurately capture all forms of SM use.

Despite limitations, the current study suggests that the BAT is a useful tool for intervening with smartphone and SM use among college students. The ability to intervene with smartphone and SM use, even acutely, is necessary for studying directly the impact of smartphone and SM use on health-related outcomes as well as provide an understanding the variables that prevent and facilitate reduction and maintenance. Further, the BAT could be an effective model for examining phenomena that are related to reduced smartphone and SM use (e.g., withdrawal and craving). More research is needed to determine the full utility of the BAT with respect to both experimental and clinical outcomes.

References

Acuff, S. F., Dennhardt, A. A., Correia, C., & Murphy, J. G. (2019). Measurement of substance-free reinforcement in addiction: A systematic review. *Clinical Psychology Review, 70,* 79-90. https://doi.org/10.1016/j.cpr.2019.04.003

Acuff, S.F., MacKillop, J., & Murphy, J. G. (2019). A cross-cultural behavioral economic analysis of compulsive internet use: Data from five countries. Paper presented at the 2019 meeting of the Association for Behavioral and Cognitive Therapies, Atlanta, GA.

American Psychiatric Association. (2013). *Diagnostic and statistical manual of mental disorders* (5th ed.). Arlington, VA: Author.

Andreassen, C. S., Torsheim, T., Brunborg, G. S., & Pallesen, S. (2012). Development of a Facebook addiction scale. *Psychological Reports, 110*(2), 501-517. doi: 10.2466/02.09.18.PR0.110.2.501-517

Benson, T. A., Little, C. S., Henslee, A. M., & Correia, C. J. (2009). Effects of reinforcer magnitude and alternative reinforcer delay on preference for alcohol during a multiple-choice procedure. *Drug and Alcohol Dependence*, *100*(1-2), 161-163. https://doi.org/10.1016/j.drugalcdep.2008.09.005

Billieux, J., Maurage, P., Lopez-Fernandez, O., Kuss, D. J., & Griffiths, M. D. (2015). Can disordered mobile phone use be considered a behavioral addiction? An update on current evidence and a comprehensive model for future research. *Current Addiction Reports, 2*(2), 156-162. doi: 10.1007/s40429-015-0054-y

Blake, H. (2008). Innovation in practice: mobile phone technology in patient care. *British Journal of Community Nursing*, *13*(4), 160-165. doi: 10.12968/bjcn.2008.13.4.29024

Buysse, D. J., Reynolds III, C. F., Monk, T. H., Berman, S. R., & Kupfer, D. J. (1989). The Pittsburgh Sleep Quality Index: a new instrument for psychiatric practice and research. *Psychiatry Research*, *28*(2), 193-213. doi: 10.1016/0165-1781(89)90047-4

Carey, K. B. (1997). Reliability and validity of the time-line follow-back interview among psychiatric outpatients: A preliminary report. *Psychology of Addictive Behaviors*, *11*(1), 26. doi: 10.1037/0893-164X.11.1.26

Carpenter, J. S., & Andrykowski, M. A. (1998). Psychometric evaluation of the Pittsburgh Sleep Quality Index. *Journal of Psychosomatic Research*, *45*(1), 5-13. doi: https://doi.org/10.1016/S0022-3999(97)00298-5

Cazzulino, F., Burke, R. V., Muller, V., Arbogast, H., & Upperman, J. S. (2014). Cell phones and young drivers: a systematic review regarding the association between psychological factors and prevention. *Traffic injury prevention*, *15*(3), 234-242. doi: 10.1080/15389588.2013.822075

Cheever, N. A., Rosen, L. D., Carrier, L. M., & Chavez, A. (2014). Out of sight is not out of mind: The impact of restricting wireless mobile device use on anxiety levels among low, moderate and high users. *Computers in Human Behavior*, *37*, 290-297. doi: 10.1016/j.chb.2014.05.002

Choliz, M. (2010). Mobile phone addiction: a point of issue. *Addiction*, *105*(2), 373-374. doi: 10.1111/j.1360-0443.2009.02854.x

Clayton, R. B., Leshner, G., & Almond, A. (2015). The extended iSelf: The impact of iPhone separation on cognition, emotion, and physiology. *Journal of Computer-Mediated Communication*, *20*(2), 119-135. doi: 10.1016/j.chb.2014.05.002

Correia, C. J., & Little, C. (2006). Use of a multiple-choice procedure with college student drinkers. *Psychology of Addictive Behaviors*, *20*(4), 445. https://doi.org/10.1037/0893-164X.20.4.445

Craig, C. L., Marshall, A. L., Sjorstrom, M., Bauman, A. E., Booth, M. L., Ainsworth, B. E., & Oja, P. (2003). International physical activity questionnaire: 12-country reliability and validity. *Medicine and Science in Sports and Exercise*, *35*(8), 1381-1395.

Dinger, M. K., Behrens, T. K., & Han, J. L. (2006). Validity and reliability of the International Physical Activity Questionnaire in college students. *American Journal of Health Education*, *37*(6), 337-343.

Elhai, J. D., Dvorak, R. D., Levine, J. C., & Hall, B. J. (2017). Problematic smartphone use: A conceptual overview and systematic review of relations with anxiety and depression psychopathology. *Journal of Affective Disorders*, *207*, 251-259. doi: 10.1016/j.jad.2016.08.030

Glass, A. L., & Kang, M. (2017). Dividing attention in the classroom reduces exam performance. *Educational Psychology*, *39*(3) 395-408. doi: 10.1080/01443410.2018.1489046

Fjeldsoe, B. S., Marshall, A. L., & Miller, Y. D. (2009). Behavior change interventions delivered by mobile telephone short-message service. *American Journal of Preventive Medicine*, *36*(2), 165-173. doi:10.1016/j.amepre.2008.09.040

Hall, J. A., Xing, C., Ross, E. M., & Johnson, R. M. (2019). Experimentally manipulating social media abstinence: Results of a four-week diary study. *Media Psychology*, 1-17. https://doi.org/10.1080/15213269.2019.1688171

Heil, S. H., Alessi, S. M., Lussier, J. P., Badger, G. J., & Higgins, S. T. (2004). An experimental test of the influence of prior cigarette smoking abstinence on future abstinence. *Nicotine & Tobacco Research*, *6*(3), 471-479.

Higgins, S. T., Badger, G. J., & Budney, A. J. (2000). Initial abstinence and success in achieving longer term cocaine abstinence. *Experimental and clinical psychopharmacology*, *8*(3), 377. doi: 10.1037//1064-1297.8.3.377

Hiniker, A., Hong, S. R., Kohno, T., & Kientz, J. A. (2016, May). Mytime: Designing and evaluating an intervention for smartphone non-use. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, 4746-4757. ACM.

Hinsch, C., & Sheldon, K. M. (2013). The impact of frequent social internet consumption: Increased procrastination and lower life satisfaction. *Journal of Consumer Behaviour*, 12, 496–505. doi:10.1002/cb.1453

Holst, A. (2019, October). iPhone users as share of smartphone users in the United States 2014-2021. Retrieved from https://www.statista.com/statistics/236550/percentage-of-us-population-that-own-a-iphone-smartphone/#targetText=Currently%20there%20are%20more%20than,users%20in%20the%20United%20States.

Hunt, M. G., Marx, R., Lipson, C., & Young, J. (2018). No More FOMO: Limiting social media decreases loneliness and depression. *Journal of Social and Clinical Psychology*, *37*(10), 751-768. doi: 10.1521/jscp.2018.37.10.751

Irons, J. G., Bassett, D. T., Prendergast, C. O., Landrum, R. E., & Heinz, A. J. (2016). Development and initial validation of the caffeine consumption questionnaire-revised. *Journal of Caffeine Research*, *6*(1), 20-25. doi: 10.1089/jcr.2015.0012

Irons, J. G., & Correia, C. J. (2008). A brief abstinence test for college student smokers: A feasibility study. *Experimental and Clinical Psychopharmacology, 16*(3), 223. doi: 10.1037/1064-1297.16.3.223

Irons, J. G., Joachim, B. T., Stanley, T. B., Rininger, A. M., & Jarvis, B. P. (2019). Assessing the utility of a brief abstinence test to initiate caffeine abstinence. *Journal of Caffeine and Adenosine Research, 9*(1), 28-34. doi: 10.1089/caff.2018.0013

Irons, J. G., Pope, D. A., Pierce, A. E., Van Patten, R. A., & Jarvis, B. P. (2013). Contingency management to induce exercise among college students. *Behaviour Change*, *30*(2), 84-95. doi: 10.1017/bec.2013.8

Kalaf, S. (2018, October). U.S. consumers time-spent on mobile crosses 5 hours a day. Retrieved from https://flurrymobile.tumblr.com/post/157921590345/us-consumers-time-spent-on-mobile-crosses-5.

Katz, E. C., Robles-Sotelo, E., Correia, C. J., Silverman, K., Stitzer, M. L., & Bigelow, G. (2002). The brief abstinence test: effects of continued incentive availability on cocaine abstinence. *Experimental and Clinical Psychopharmacology, 10*(1), 10. doi: 10.1037/1064-1297.10.1.10

Kim, S. E., Kim, J. W., & Jee, Y. S. (2015). Relationship between smartphone addiction and physical activity in Chinese international students in Korea. *Journal of Behavioral Addictions*, *4*(3), 200-205. doi: 10.1556/2006.4.2015.028

Kruger, D. J., & Djerf, J. M. (2016). High ringxiety: Attachment anxiety predicts experiences of phantom cell phone ringing. *Cyberpsychology, Behavior, and Social Networking*, *19*(1), 56-59. doi: 10.1089/cyber.2015.0406

Kuss, D. J., & Griffiths, M. D. (2011). Online social networking and addiction—a review of the psychological literature. *International Journal of Environmental Research and Public Health, 8*(9), 3528-3552. doi:10.3390/ijerph8093528

Lapierre, M. A., Zhao, P., & Custer, B. E. (2019). Short-term longitudinal relationships between smartphone use/dependency and psychological well-being among late adolescents. Journal of Adolescent Health, 1-6. doi: https://doi.org/10.1016/j.jadohealth.2019.06.001

Lepp, A., Barkley, J. E., Sanders, G. J., Rebold, M., & Gates, P. (2013). The relationship between cell phone use, physical and sedentary activity, and cardiorespiratory fitness in a sample of U.S. college students. *International Journal of Behavioral Nutrition and Physical Activity, 10(*1), 79. doi:10.1186/1479-5868-10-79

Li, X., Newman, J., Li, D., & Zhang, H. (2016). Temperament and adolescent problematic Internet use: The mediating role of deviant peer affiliation. *Computers in Human Behavior*, *60*, 342-350. doi: https://doi.org/10.1016/j.chb.2016.02.075

Löchtefeld, M., Böhmer, M., & Ganev, L. (2013, December). AppDetox: helping users with mobile app addiction. In *Proceedings of the 12th International Conference on Mobile and Ubiquitous Multimedia,* 43. ACM.

Macale, S. (2019, November). 98% of online US adults aged 18-24 use social media. Retrieved from https://thenextweb.com/socialmedia/2011/10/08/98-of-online-us-adults-aged-18-24-use-social-media/

Malott, R. W., & Svinicki, J. G. (1969). Contingency management in an introductory psychology course for one thousand students. *The Psychological Record, 19*(4), 545-556. doi: 10.1007/BF03393885

Metzger, R. L. (1976). A reliability and validity study of the state-trait anxiety inventory. *Journal of Clinical Psychology, 32*(2), 276-278.

Nandakumar, R., Gollakota, S., & Sunshine, J. E. (2019). Opioid overdose detection using smartphones. *Science Translational Medicine, 11*(474). doi: 10.1126/scitranslmed.aau8914

National Safety Council (2019, May 8). Ending distracted driving is everyone's responsibility. Retrieved from https://www.nsc.org/road-safety/safety-topics/distracted-driving

Oberst, U., Wegmann, E., Stodt, B., Brand, M., & Chamarro, A. (2017). Negative consequences from heavy social networking in adolescents: The mediating role of fear of missing out. *Journal of Adolescence, 55*, 51-60. doi: 10.1016/j.adolescence.2016.12.008

Oviedo-Trespalacios, O., Nandavar, S., Newton, J. D. A., Demant, D., & Phillips, J. G. (2019). Problematic Use of Mobile Phones in Australia… Is It Getting Worse?. *Frontiers in Psychiatry*, *10*. doi: 10.3389/fpsyt.2019.00105

Perrin, A. (2018, October). 10 facts about smartphone as the iPhone turns 10. Retrieved from http://www.pewresearch.org/fact-tank/2017/06/28/10-facts-about-smartphones/.

Petry, N. M., Martin, B., Cooney, J. L., & Kranzler, H. R. (2000). Give them prizes and they will come: Contingency management for treatment of alcohol dependence. *Journal of Consulting and Clinical Psychology*, *68*(2), 250. doi: 10.1037/0022-006X.68.2.250

Przybylski, A. K., Orben, A., & Weinstein, N. (2019). How much is too much? Examining the relationship between digital screen engagement and psychosocial functioning in a confirmatory cohort study. *Journal of the American Academy of Child & Adolescent Psychiatry*. doi: https://doi.org/10.1016/j.jaac.2019.06.017

Roberts, J., Yaya, L., & Manolis, C. (2014). The invisible addiction: Cell-phone activities and addiction among male and female college students. *Journal of Behavioral Addictions*, *3*(4), 254-265. doi: 10.1556/JBA.3.2014.015

Robinson, A., Bonnette, A., Howard, K., Ceballos, N., Dailey, S., Lu, Y., & Grimes, T. (2019). Social comparisons, social media addiction, and social interaction: An examination of specific social media behaviors related to major depressive disorder in a millennial population. *Journal of Applied Behavioural Research*. doi: 10.1111/jabr.12158

Robles, E., Silverman, K., Preston, K. L., Cone, E. J., Katz, E., Bigelow, G. E., & Stitzer, M. L. (2000). The brief abstinence test: Voucher-based reinforcement of cocaine abstinence. *Drug and Alcohol Dependence, 58*(1-2), 205-212. doi: 10.1016/S0376-8716(99)00090-3

Romanowich, P., & Lamb, R. J. (2014). The effects of percentile versus fixed criterion schedules on smoking with equal incentive magnitude for initial abstinence. *Experimental and clinical psychopharmacology*, *22*(4), 348.

Rosen, M. I., Dieckhaus, K., McMahon, T. J., Valdes, B., Petry, N. M., Cramer, J., & Rounsaville, B. (2007). Improved adherence with contingency management. *AIDS Patient Care and STDs*, *21*(1), 30-40. doi: 10.1089/apc.2006.0028

Samaha, M., & Hawi, N. S. (2016). Relationships among smartphone addiction, stress, academic performance, and satisfaction with life. *Computers in Human Behavior*, *57*, 321-325. doi: 10.1016/j.chb.2015.12.045

Sampasa-Kanyinga, H., & Lewis, R. F. (2015). Frequent use of social networking sites is associated with poor psychological functioning among children and adolescents. *Cyberpsychology, Behavior, and Social Networking*, *18*(7), 380-385. doi: https://doi.org/10.1089/cyber.2015.0055

Sayegh, C. S., Huey Jr, S. J., Zara, E. J., & Jhaveri, K. (2017). Follow-up treatment effects of contingency management and motivational interviewing on substance use: A meta-analysis. *Psychology of Addictive Behaviors*, *31*(4), 403. doi: 10.1037/adb0000277

Sigmon, S. C., Correia, C. J., & Stitzer, M. L. (2004). Cocaine abstinence during methadone maintenance: effects of repeated brief exposure to voucher-based reinforcement. *Experimental and Clinical Psychopharmacology*, *12*(4), 269. doi: 10.1037/1064-1297.12.4.269

Smith, A., & Anderson, M. (2019, November) Social media use in 2018. Retrieved from https://www.pewresearch.org/internet/2018/03/01/social-media-use-in-2018/

Sobell, L. C., Brown, J., Leo, G. I., & Sobell, M. B. (1996). The reliability of the Alcohol Timeline Followback when administered by telephone and by computer. *Drug & Alcohol Dependence*, *42*(1), 49-54. doi: 10.1016/0376-8716(96)01263-X

Spielberger, C. D., Gorsuch, R. L., Lushene, R. E., & Vagg, P. R. (2010). State-trait anxiety inventory (STAI). *BiB*, *1970*, 180. doi: 10.1002/9780470479216.corpsy0943

Steiger, J. H., & Fouladi, R. T. (1992). R2: A computer program for interval estimation, power calculations, sample size estimation, and hypothesis testing in multiple regression. *Behavior Research Methods*, 24(4), 581-582.

Stieger, S., & Lewetz, D. (2018). A week without using social media: Results from an ecological momentary intervention study using smartphones. *Cyberpsycholgy, Behavior, and Social Networking*, 21(10), 618–624. doi:10.1089/cyber.2018.0070

Stewart, S. H., Zeitlin, S. B., & Samoluk, S. B. (1996). Examination of a three-dimensional drinking motives questionnaire in a young adult university student sample. *Behaviour Research and Therapy*, *34*(1), 61-72. doi: 10.1016/0005-7967(95)00036-W

The 25 Scariest Texting and Driving Accident Statistics. (2019, May 8). Retrieved from https://www.icebike.org/texting-and-driving/

Thomée, S., Härenstam, A., Hagberg, M. (2011) Mobile phone use and stress, sleep disturbances, and symptoms of depression among young adults – a prospective cohort study. *BMC Public Health, 11*(1), 66.

Turel, O., Cavagnaro, D. R., & Meshi, D. (2018). Short abstinence from online social networking sites reduces perceived stress, especially in excessive users. *Psychiatry Research*, 270, 947–953. doi:10.1016/j.psychres.2018.11.017

Van Patten, R. A., Irons, J. G., & Apple, K. J. (2015). Contingency Management to Increase Grade Point Average Among Fraternity Members: A Feasibility Study. *Journal of College Student Development*, *56*(2), 176-180. doi: 10.1353/csd.2015.0020

Volpp, K. G., John, L. K., Troxel, A. B., Norton, L., Fassbender, J., & Loewenstein, G. (2008). Financial incentive–based approaches for weight loss: a randomized trial. *JAMA*, *300*(22), 2631-2637. doi: 10.1001/jama.2008.804

Ward, A. F., Duke, K., Gneezy, A., & Bos, M. W. (2017). Brain drain: The mere presence of one’s own smartphone reduces available cognitive capacity. *Journal of the Association for Consumer Research*, *2*(2), 140-154. doi: https://doi.org/10.1086/691462

Watson, D., Clark, L. A., & Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: the PANAS scales. *Journal of Personality and Social Psychology*, *54*(6), 1063. doi: http://dx.doi.org/10.1037/0022-3514.54.6.1063

Wurmser, J. (2018, October). Mobile time spent 2018. Retrieved from https://www.emarketer.com/content/mobile-time-spent-2018

Tables

Table 1.

Participant Descriptive Statistics

	Min	Max	*M*	*SD*
GPA	1.74	3.87	3.07	0.57
HPD playing games on phone	1.00	7.00	2.08	1.55
HPD playing games on console	0.00	4.00	1.78	1.20
HPD using SM per day	2.00	10.00	4.47	2.08
HPD watching TV	0.00	8.00	3.08	1.87

Note. HPD = hours-per-day.

Table 2.
Participant Descriptive Statistics Throughout the Study

	Intake		Post-BAT		3-weeks post-BAT	
	M	*SD*	*M*	*SD*	*M*	*SD*
DMQ-Social	14.72	5.81	12.08	6.18	13.08	5.49
DMQ-Coping	8.81	4.38	8.73	3.91	8.13	3.73
DMQ-Enhance	13.34	5.62	13.69	6.03	12.08	5.51
DMQ-Conform	7.31	2.75	7.39	3.10	7.12	3.14
SMASI Total	49.41	13.36	42.58	13.55	42.04	12.40
SAS-SV Total	35.16	11.13	30.54	12.50	30.96	12.27
TLFB Total	6.28	6.23	6.27	6.87	2.29	3.56
PSQI Global	7.88	2.86	8.35	2.53	8.50	3.44
PANAS Positive Affect	25.88	10.89	25.13	10.77	26.46	11.84
PANAS Negative Affect	15.47	6.50	13.96	3.89	14.74	6.45
STAI State Anxiety	42.37	11.84	41.36	10.83	40.45	10.87
STAI Trait Anxiety	43.86	9.49	42.58	8.71	43.04	12.21
CCQ-R Weekly Caffeine Use (in mg)	1248.80	1133.36	1047.77	1400.52	776.69	1019.54
IPAQ-SF Weekly Vigorous PA (in min)	107.80	124.08	76.04	41.57	65.00	35.62
IPAQ-SF Weekly Moderate PA (in min)	92.29	70.96	98.33	98.92	99.71	80.90

Table 3.
Screener Descriptive Statistics of all Measures

	N	Min	Max	*M*	*SD*
Age	398	17.00	82.00	19.32	3.44
GPA	398	0.15	4.00	3.09	0.57
HPD watching TV	362	0.00	19.00	3.01	2.29
HPD using SM	413	0.00	16.00	3.97	2.58
HPD playing video games	156	0.00	10.00	2.01	1.77
HPD playing phone games	353	0.00	10.00	1.88	1.53
DMQ - Social	353	5.00	25.00	13.35	5.83
DMQ - Coping	360	5.00	25.00	8.19	4.07
DMQ - Enhance	360	8.00	30.00	16.41	6.01
DMQ - Conform	358	5.00	25.00	7.03	2.93
SMASI Total	360	18.00	90.00	40.46	15.14
SAS-SV Total	355	10.00	70.00	32.38	12.03
TLFB Total	352	0.00	83.00	5.71	8.68
PSQI Global	353	2.00	22.00	8.29	3.44
PANAS Positive Affect	360	10.00	50.00	28.48	9.03
PANAS Negative Affect	360	10.00	47.00	16.82	6.55
STAI State Anxiety	331	20.00	78.00	42.67	11.95
STAI Trait Anxiety	339	22.00	72.00	42.12	9.90
CCQ-R Weekly Caffeine Use (in mg)	360	0.00	26042.16	1135.83	1721.22
IPAQ-SF Weekly Vigorous PA (min)	354	0.00	7200.00	284.77	582.53
IPAP-SF Weekly Moderate PA (min)	340	0.00	248.00	29.98	45.77

Note. HPD = hours-per-day.

Table 4.
BAT Contingencies and Payment Incentives

Session	Intake	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	3-week follow-up
Contingent Behavior	--	-30% (20)	-40% (26)	-50% (33)	-50% (33)	-50% (33)	-50% (33)	-50% (33)	--
Contingency Payment	$5	$10	$10	$10	$10	$10	$10	$10	--
Data Upload Payment	--	$1.50	$1.50	$1.50	$1.50	$1.50	$1.50	$1.50	$10
Totals	$5	$11.25	$11.25	$11.25	$11.25	$11.25	$11.25	$11.25	$10

Note. Percentages reflect required reduction from baseline usage calculated during intake. At least 2/3 of the total reduction (indicated in parentheses) must be attributable to SM use in order to meet BAT criteria.

Table 5.

Outcomes of SM Use for Screener

Predictor: Self-Reported SM Use		*b*	*SE*	CI 95% of *b*	R^2	CI 95% of R^2
IPAQ-SF Vigorous PA		27.52	12.40	[3.13, 51.91]	.01	[.00, .05]
DMQ-Coping		0.27	0.09	[0.10, 0.44]	.03	[.00, .07]
DMQ-Enhance		0.26	0.13	[0.00, 0.51]	.01	[.00, .04]
CCQ-R Weekly Caffeine Use (in mg)		111.79	36.12	[40.76, 182.83]	.03	[.00, .07]
SAS-SV		1.30	0.25	[0.82, 1.79]	.07	[.03, .14]
SMASI	Salience	0.31	0.06	[0.20, 0.42]	.08	[.03, .14]
	Tolerance	0.26	0.06	[0.15, 0.38]	.05	[.02, .11]
	Mood Modification	0.28	0.07	[0.15, 0.41]	.05	[.02, .10]
	Relapse	0.23	0.06	[0.11, 0.35]	.04	[.01, .08]
	Withdrawal	0.27	0.06	[0.14, 0.39]	.05	[.01, .08]
	Conflict	0.21	0.06	[0.09, 0.34]	.03	[.02, .10]
	Total Scores	1.57	0.31	[0.97, 2.18]	.07	[.03, .13]

Note. Confidence intervals for R^2 computed using R2 program (Steiger & Fouladi, 1992).

Table 6.
Descriptive Statistics of Smartphone Use (in Min) During the BAT

	N	Min	Max	*M*	*SD*
Baseline	32	147.00	705.00	331.50	131.78
Day 1	31	34.00	457.00	165.08	91.86
Day 2	31	20.00	520.00	167.45	109.55
Day 3	31	19.00	332.00	144.73	85.24
Day 4	29	33.00	419.00	173.89	103.53
Day 5	30	14.00	592.00	193.62	120.79
Day 6	28	0.00	438.00	174.08	113.02
Day 7	31	27.00	455.00	193.94	111.16

Table 7.
Descriptive Statistics of SM Use (in Min) During the BAT

	N	Min	Max	*M*	*SD*
Baseline	32	26.00	400.00	147.16	77.00
Day 1	32	4.00	169.00	65.78	47.60
Day 2	32	4.00	329.00	71.31	63.49
Day 3	31	5.00	219.00	67.84	55.16
Day 4	30	4.00	207.00	76.20	58.34
Day 5	31	3.00	225.00	77.94	61.65
Day 6	27	0.00	236.00	73.48	58.86
Day 7	28	4.00	365.00	115.35	91.66

Table 8.
Correlations of Health Variables with Baseline Smartphone, SM Use, and Self-Reported SM Use

	Baseline Smartphone Use		Baseline SM Use		Self-Report SM Use	
	r	*p*	*r*	*p*	*r*	*p*
GPA	-.38	.032	-.07	.707	-.04	.818
CCQ-R Weekly Caffeine Use	-.15	.400	.14	.441	.004	.981
SMASI Total Scores	-.08	.599	.23	.212	.10	.578
SAS-SV Total Scores	-.02	.922	-.03	.855	.07	.695
DMQ - Social	-.10	.585	-.05	.803	-.30	.094
DMQ - Coping	.00	.986	.12	.499	-.12	.522
DMQ - Conform	-.03	.865	.02	.926	-.19	.298
DMQ - Enhance	-.12	.516	.07	.721	-.22	.224
PANAS Positive Affect	-.26	.157	.07	.695	.06	.752
PANAS Negative Affect	.04	.849	-.03	.881	-.12	.515
STAI Trait Anxiety	.24	.212	.10	.613	-.19	.329
PSQI Sleep Quality	.01	.975	-.24	.195	.08	.661
IPAQ-SV Weekly Vigorous PA	.11	.595	-.05	.804	.30	.151
IPAQ-SV Weekly Moderate PA	.004	.986	.24	.253	.12	.588
TLFB Total	.04	.840	-.02	.913	-.07	.702

Note. Baseline Smartphone and SM Use were recorded via ScreenTime at Intake. Self-report SM use was recorded at screening.

Table 9.
Correlates of Smartphone and SM Use

Relations	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
Smartphone Use, SM Use	.59	.82	.73	.73	.67	.80	.90
Notifications, Pickups	.69	.71	.71	.79	.80	.91	.64
Smartphone Use, Pickups	.42	.31	.35	.52	.50	.49	.55
SM Use, Pickups	.64	.33	.40	.71	.50	.57	.57
Smartphone Use, Notifications	.17	.05	.10	.28	.49	.53	.53
SM Use, Notifications	.42	.07	.26	.53	.36	.53	.67

Table 10.
Predicting BAT Efficacy with Health-Related Variables

	R^2	R^2_{Δ}	CI 95% of R^2	*b*	CI 95% of *b*
Model 1					
Step 1: GPA	.14	.14	[.00, .41]	1.23	[-0.32, 2.78]
Step 2: DMQ-Enhance	.18	.04	[.00, .43]	0.17	[-0.02, 0.37]
Step 3: STAI State Anxiety	.21	.03	[.03, .44]	0.01	[-0.12, -.14]
Step 4: SMASI-Relapse	.29	.08	[.00, .50]	-0.30	[-0.70, 0.10]
Step 5: PANAS Negative Affect	.29	.00	[.00, .48]	0.03	[-0.26, 0.20]
Model 2					
Step 1: GPA	.15	.15	[.00, .41]	1.21	[-0.14, 2.55]
Step 2: DMQ-Enhance	.20	.05	[.00, .44]	-0.33	[0.02, 0.34]
Step 3: SMASI-Relapse	.32	.12	[.05, .55]	0.18	[-0.62, -0.03]

Note. $n_{\text{model1}} = 29$, $n_{model2} = 31$. R^2 confidence intervals obtained using R2 program (Steiger & Fouladi, 1992).

Table 11.
Predicting Smartphone Use Change with Health-Related Variables

	R^2	R^2_Δ	CI 95% of R^2	*b*	CI 95% of *b*
Step 1: SAS-SV Total	.009	.009	[.00, .01]	-0.165	[-1.80, 1.47]
Step 2: DMQ-Enhance	.05	.04	[.00, .08]	-1.56	[-4.65, 1.52]
Step 3: STAI State Anxiety	.08	.03	[.00, .10]	0.15	[-1.89, 2.18]
Step 4: PANAS Negative Affect	.09	.01	[.00, .12]	0.91	[-2.68, 4.51]

Note. n = 28. R^2 confidence intervals obtained using R2 program (Steiger & Fouladi, 1992).

Table 12.
Predicting SM Use Change With Health Variables

	R^2	R^2_{Δ}	CI 95% of R^2	*b*	CI 95% of *b*
Step 1: GPA	.14	.14	[.00, .43]	27.73	[-11.92, 67.38]
Step 2: DMQ-Social	.26	.12	[.02, .53]	3.07	[-3.58, 9.73]
Step 3: DMQ-Enhance	.26	.002	[.00, .50]	0.52	[-6.82, 7.85]
Step 4: SAS-Total	.29	.03	[.00, .51]	1.43	[-1.21, 4.06]
Step 5: PSQI Sleep Quality	.32	.03	[.00, .54]	-3.75	[-11.72, 4.24]

Note. n = 27. R^2 confidence intervals obtained using R2 program (Steiger & Fouladi, 1992).

Figures

Figure 1.

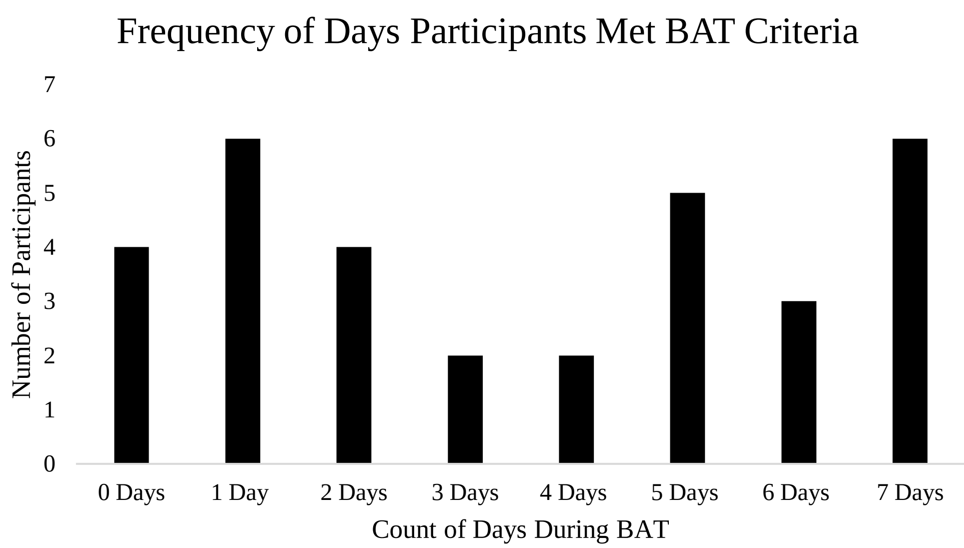

Figure 1. N = 32.

Figure 2.

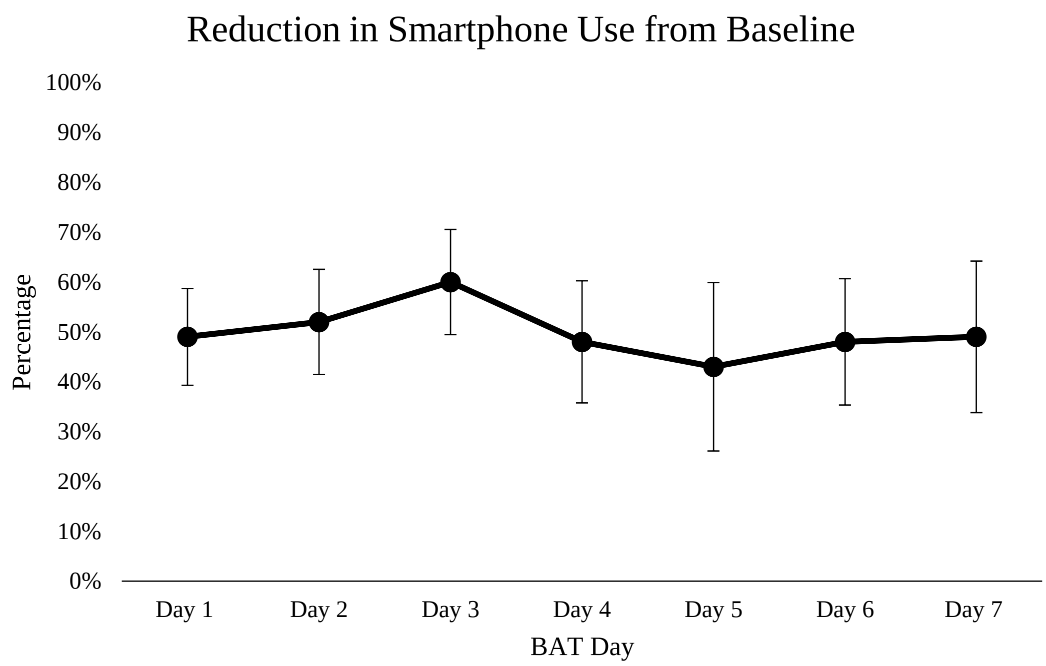

Figure 2. Data points represent the average percentage reduction in smartphone use from baseline. Error bars represent the 95% CI for each BAT day.

Figure 3.

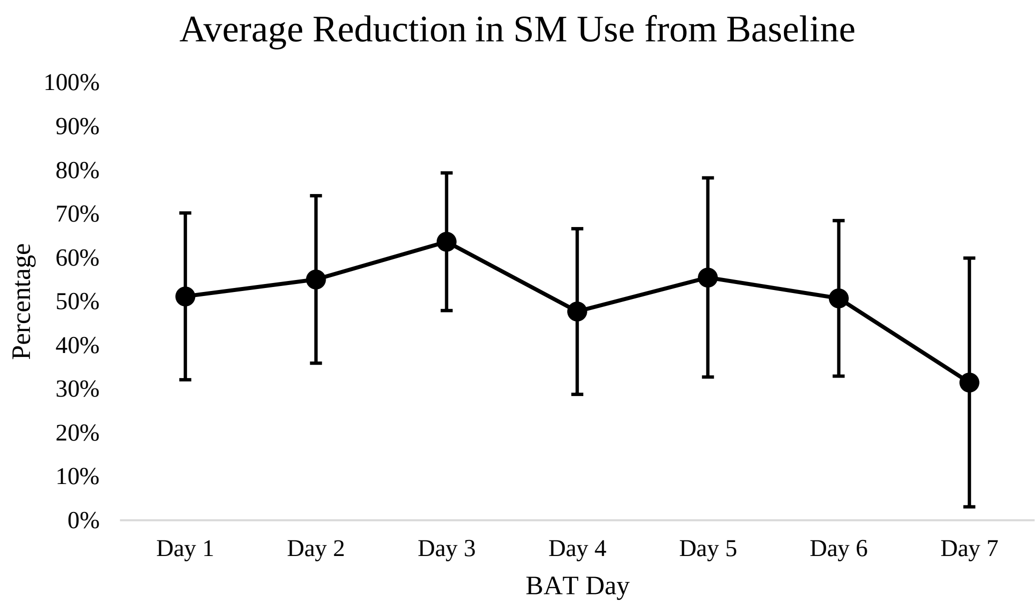

Figure 3. Data points represent the average percentage reduction in SM use from baseline. Error bars represent the 95% CI for each BAT day.

Figure 4.

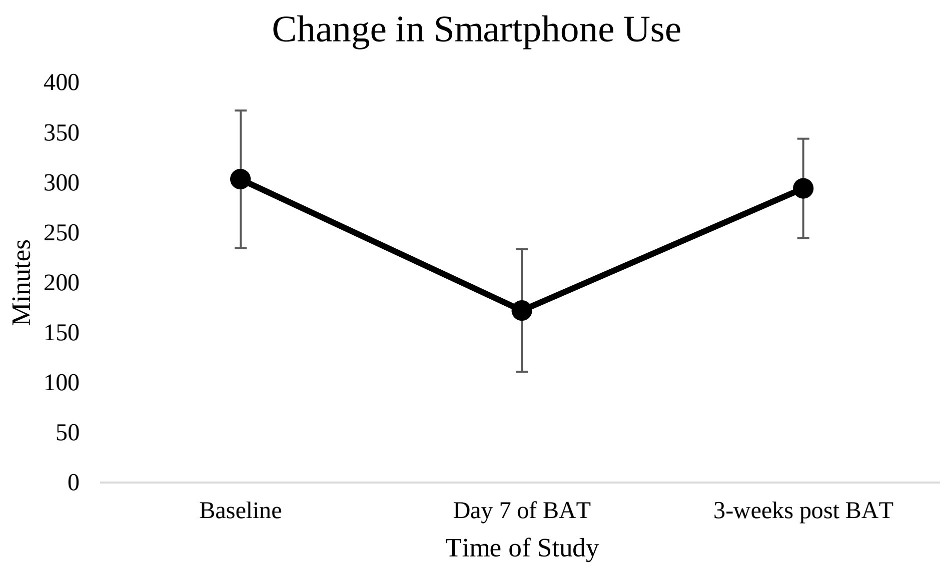

Figure 4. On average, participants reduced smartphone use by 200.26 min from Baseline to the end of the BAT, and increased smartphone use by 191.26 min from the end of the BAT to 3-weeks post BAT. Error bars represent the 95% CI at each time point.

Figure 5.

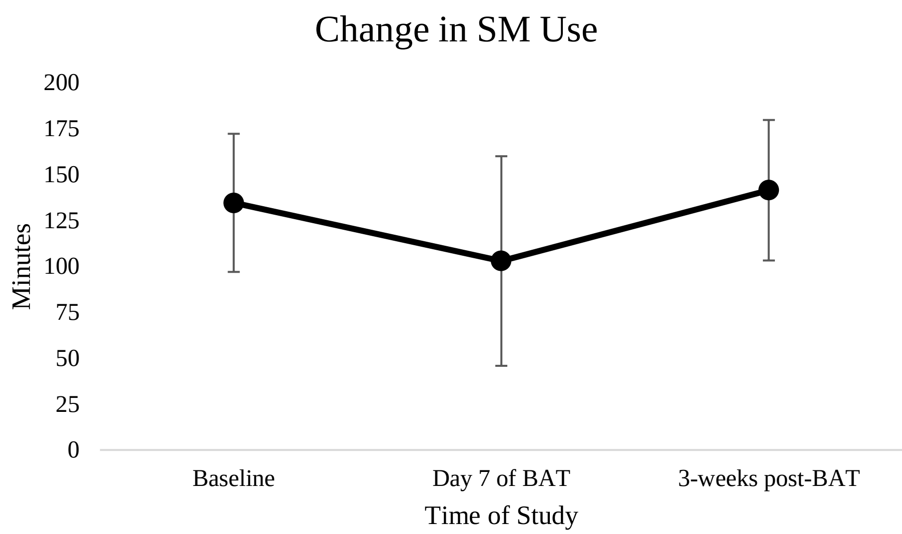

Figure 5. No differences in SM use were observed between intake, Day 7 of the BAT, and 3-weeks post-BAT. Error bars represent the 95% CI at each time point.

Footnotes

[1] Using smartphones while driving is believed to have caused an estimated 1.5 million accidents in the United States in 2018 and approximately 11 teenagers die in driving accidents daily as a result of texting while driving.

[2] Of the few studies attempting to modify smartphone use, researchers relied on self-report to verify behavior change and/or assess techniques for how individuals were attempting to modify smartphone use during intervention (e.g., self-regulation, turning off phones, deleting or limiting app use, etc.; Ko et al., 2015). Some researchers have developed third-party applications to attempt to verify phone use and allow users to set restrictions on phone or app use (Löchtefeld, Böhmer, & Ganev, 2013; Hiniker, Hong, Kohno, & Kientz, 2016); however, researchers were only interested in testing the efficacy of the newly-developed third party application in its ability to respond to user-determined preferences. Researchers did not examine how best to modify smartphone or SM use and did not demonstrate that phone use can be manipulated experimentally.

[3] While Hunt et al. (2018) provide compelling data that SM use can be manipulated experimentally and verified with means other than self-report, the Battery Life feature on iPhones (used as means to verify use) clears usage data when the phone is rebooted so data may not accurately reflect usage when submitted to researchers. Lastly, Battery Life only provides the number of minutes users spend on apps (restricting data associated with app use).

[4] One concern with any behavioral intervention (including CM) is cost-effectiveness. CM can be taxing on the amount of resources (e.g., time, money) needed to implement the procedure depending on how frequently researchers assess behavior change and the magnitude of the incentive participants receive for meeting target behaviors. Data suggest that participants are

more likely to respond to CM procedures when offered higher incentives (Lussier, Heil, Mongeon, Badger, & Higgins, 2006); however, cost-effectiveness must also be considered. Therefore, in addition to determining *if* CM can be utilized to initiate change of a particular behavior, researchers must also consider minimally effective and optimal parameters that best promote behavior change while *also* minimizing cost so that CM can be utilized in clinical settings where treatment budgets are oftentimes limited.

Appendix A

Instructions for Capturing Phone Data

***Before beginning, make sure that you have the Google Drive App downloaded and you are logged into your Google Drive file with the email account that you shared with us for the study*. If you have any questions during this process, feel free to email our lab (ironsresearchlab@gmail.com).**

1. Make sure that the Screen Recording function is in your iPhone Control Center (i.e., the features that display when you swipe up on your phone when it is unlocked).

 - If it is not, go to *Settings* -- *Control Center* -- *Customize Controls* -- Scroll down to Screen Recording and touch the green plus sign.

2. Please make sure that you are in the scheduled time window that we asked you to upload your data (between 9pm-11:59pm).

3. Unlock your iPhone and go to *Settings* -- *Screen Time* and wait until your current daily phone use data pops up at the top (may take a few seconds to refresh).

4. Swipe up on your phone, and touch the Screen Recording button (looks like a bullseye). This feature will count down from 3 and then begin taking a video of your iPhone screen.

5. Once the screen video begins, leave your phone on the Screen Time page for five seconds so that we can record your overall daily use time and social networking daily use time.

6. Touch the bar that details your phone usage (where Screen Time displays the total amount of time you've been on your phone today).

7. When you get to the next page, leave this page pulled up on your phone for five seconds.

8. Slowly scroll down the page until you get to *Pickups*. Keep scrolling down until you can see *Most Pickups*. Leave your screen alone on this page for five seconds.

9. Continue to scroll down until you reach *Notifications*. When you are able to see how many notifications you have received today please stop scrolling and leave your phone idle for five seconds.

10. Exit out of the *Settings* application (hit the Home button) and touch the Screen Recording function in your Control Center. This will end your screen recording and will save the recording to *Photos.*

11. You are now going to upload this video to *Google Drive*. Open the Google Drive application, select your study folder, click the blue plus at the bottom right of your screen, select *Upload,* and then select *Photos and Videos*.

12. Select your screen recording and it should upload to the folder. **After it uploads, select the three gray dots on your upload, scroll down and select Rename, and rename the file Participant#_date (actually write in your participant number and the real date).**

13. Repeat the same steps each day. Thank you!!

Appendix B

Predictors of SM use.

We used screener data to analyze whether self-reported SM use predicted health-related outcomes. A series of simple linear regression analyses revealed that increasing self-reported SM use predicted increases in participants' self-reported engagement in vigorous physical activity, DMQ-coping scores, DMQ-enhance scores, weekly caffeine consumption, all SMASI subscores and total scores, and SAS-SV scores in our sample (R^2 range = .01 - .08; see Table 5 for regression coefficients and other statistical information).

Group comparisons.

We separated cases into three groups: individuals who participated in the study (*n* = 32), individuals who qualified for the study (and were invited to participate) but elected to not participate (*n* = 47), and individuals who did not qualify for the study based on eligibility criteria (*n* = 339). A series of one-way ANOVAs revealed that the three groups did not differ with respect to demographic variables (i.e., age, GPA), hours spent on electronic platforms (i.e., video games, cell phone games, social media, watching TV), or health-related variables, observed power range = .061 - .288.