NEURAL AND BEHAVIORAL EVIDENCE FOR A LINK BETWEEN MOBILE TECHNOLOGY ENGAGEMENT AND INTERTEMPORAL PREFERENCE

A Dissertation
Submitted to
the Temple University Graduate Board

In Partial Fulfillment
of the Requirements for the Degree
DOCTOR OF PHILOSOPHY

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by
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August 2017

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ABSTRACT

Mobile electronic devices such as smartphones are playing an increasingly pervasive role in our daily activities. A growing body of literature is beginning to investigate how mobile technology habits might relate to individual differences in cognitive traits. The present study is an investigation into how individual differences in intertemporal preference, impulse control, and reward sensitivity, are predictive of the degree to which people engage with their smartphones, in two separate experiments. Experiment 1 utilized behavioral and self-reported measures for each of the aforementioned cognitive traits to examine their relationships with Mobile Technology Engagement (MTE) as defined in Wilmer & Chein (2016). The results replicated earlier work demonstrating that mobile technology engagement is positively correlated with a tendency to discount delayed rewards. A positive relationship was also observed between MTE and reward sensitivity. In an attempt to investigate the neural origins of the relationship observed in Experiment 1, Experiment 2 examined the association between mobile technology usage and white matter connectivity from the ventral striatum (vSTR) to the ventromedial prefrontal cortex (vmPFC) and dorsolateral prefrontal cortex (dlPFC), pathways that have been previously implicated as biological markers for individual differences in intertemporal preference. Regression analyses revealed that both pathways predicted delay discounting performance, but only vSTR-vmPFC predicted mobile technology engagement. Taken together, the results of these two experiments provide important foundational evidence for both neural and cognitive factors that predict how individuals engage with mobile technology.

For Mom & Dad

ACKNOWLEDGEMENTS

This dissertation and the culmination of my graduate school experience at Temple University would not have been possible without the guidance and support of so many amazing people in my life. First and foremost, to my advisor Jason Chein, thank you for everything you have done to help me along with this process over the last five years. Beginning with your willingness to accept me into the lab and helping me devise my first-year project, continuing through my first conference presentation, my first scientific publication, my preliminary paper, and now finally this dissertation project, I simply could not have done any of it without all of your guidance and help along the way. A big thank you is also due to my core committee members, Ingrid Olson and Tom Olino, for guiding me through this project and helping me strengthen the research and the writing herein. Thank you also to my readers, Larry Steinberg, Bob Weisberg, and Vinod Venkatraman. You have all made such incredible impressions on me and I feel so fortunate to have you all playing a part in this project. Beyond my committee members, every professor with whom I have taken a class at Temple has helped shape me into the researcher I am today, and thereby contributed to this project – especially Tom Gould, Vinay Parikh, Nora Newcombe, and Phil Kendall. Further, the staff within the psychology department, especially Vanessa Allen-Smith, has been such a huge help in tackling all the administrative hurdles along the way.

My labmates at Temple quickly became lifelong invaluable friends, mentors, and sources of support. Thank you so much to Gail Rosenbaum, Kara Blacker, Ashley Smith, Karla Fettich, and Jamielyn Samper for always being there to provide help in any way you could, and for sharing a lot of fun and laughter along the way.

Thank you to my family – Mom, Dad, Jack, Julie, Kristy, Matt, Johnny, Nicholas, Annie, and Henry – for all of your unconditional love and encouragement every step of the way. And of course, thank you to Taylor. You are always my best friend, my biggest supporter, and my closest confidant. Thank you for always pushing me to be the best version of myself.

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INTRODUCTION

With every passing year, and every new product release, electronic devices are becoming increasingly portable and convenient, providing nearly constant (and ever more efficient) access to the Internet and a diverse range of software applications and digital media (Michaud & Free, 2017; Yan, 2017). With this ease of access, technology is playing an increasingly large role in our mental lives, serving as a form of “extended cognition” (Barr, Pennycook, Stolz, & Fugelsang, 2015; Clark & Chalmers, 2002; Clayton, Leshner, & Almond, 2015). This situation is a double-edged sword: while it provides us with rewarding opportunities to communicate, learn, and entertain ourselves, it also makes it difficult to resist our impulses to do so (even when engaging with technology is likely to detract from other ongoing activities). Notifications built into smartphones and other e-devices can intrude on three of our five senses, with lights, tones, and vibrations each beckoning us to extricate ourselves from our current tasks and engage instead with the device. Even in the absence of notifications, internal and external cues (thinking about work or a social relationship, a “phantom-vibration” in your leg, noticing others on their phones, etc.) provide regular reminders of the opportunity to engage with the digital world in your pocket. These frequent intermittent notifications and cues, and the relative immediacy with which we can acquire information and satisfy specific desires by responding to them, may alter our basic cognitive and affective functioning.

These regular intrusions into ongoing cognition could present a challenge to the self-regulatory impulse control processes that support the maintenance of goal-directed behaviors. In addition, by offering an often-gratifying escape from ongoing tasks, interactions with e-devices may engage basic reward-related processes and even impact the fundamental mechanisms through which we valuate and process rewards (Atchley & Warden, 2012; Sherman, Payton, Hernandez, Greenfield, & Dapretto, 2016). Indeed, some have argued that today's youth – referred to at times in the popular media as the "Now Generation" and "Generation C" ("Introducing Generation C: Americans 18-34 Are the Most Connected," 2012), having grown up in an era in which mobile technology is omnipresent – possess an especially strong need for instant gratification, which has diminished their ability to plan effectively for the future (Muther, 2013). Such assertions are part of a larger movement generally espousing the potential cognitive burdens of technology access and use (Bauerlein, 2008; Ellison, 2012; Greenfield, 2013; Sutter, 2012). Unfortunately, most of the relevant assertions (e.g., today's youth are more immediacy oriented) are based principally on anecdote, while empirical evidence regarding any relationship between technology habits and delay of gratification (or other aspects of cognition) is still quite limited. Some foundational work, such as that of Atchley & Warden (2012), shows that the discounting function that determines individuals' willingness to delay a response to informational prompts (to text or call someone back) maintains the same shape as their willingness to delay the receipt of monetary rewards. These findings indicate that technology behaviors can be understood in terms of frequently researched decision-making processes (i.e. intertemporal preference), though the specific mechanisms that are most directly linked to regular technology use remain poorly understood.

Prior research on intertemporal preference (Kalenscher & Pennartz, 2008; Peters & Büchel, 2011; Wouter van den Bos & McClure, 2013) has established that individual differences in the inclination to forego a smaller near-term reward in favor of a larger delayed reward (i.e. to delay gratification) relate to the behavior of two interacting systems: one governing the capacity to control impulses and the other influencing the individual's sensitivity to immediately available rewards (McClure, Laibson, Loewenstein, & Cohen, 2004). Put differently, the tendency to seek immediate gratification can be explained by a combination of weak impulse control (i.e., the inability to withhold a reactive or reflexive response in favor of more deliberative actions; (Ainslie, 1975)) and greater reward sensitivity (i.e., the tendency to seek out novel or rewarding sensations and to experience greater sensation upon acquiring a reward (Carver & White, 1994)).

As the opportunities for technology use have grown, so too has a body of literature investigating the resultant cognitive and behavioral impacts of such use (cf Baumgartner, Weeda, van der Heijden, & Huizinga, 2014; Hadar, Eliraz, Lazarovits, Alyagon, & Zangen, 2015; Minear, Brasher, McCurdy, Lewis, & Younggren, 2013; Ralph, Thomson, Seli, Carriere, & Smilek, 2014; Wang & Tchernev, 2012). Understandably, a significant area of focus in recent research is the safety implications of using a cellphone while driving (e.g. Atchley, Atwood, & Boulton, 2011; Strayer & Drews, 2007). For example, work in this field has demonstrated that individuals who have a tendency to text on their cellphone while driving show a steeper discounting function compared to those who do not (Hayashi, Russo, & Wirth, 2015). That is, those who more frequently engage in this dangerous behavior are also generally less inclined to delay gratification in favor of a larger, later reward. This work shows that at least one technology-related habit – texting while driving – is related to variation in intertemporal preference.

Additional clues come from work by Pearson and colleagues (Pearson, Murphy, & Doane, 2013) and Sanbonmatsu et al. (2013). As in the aforementioned studies, Pearson and colleagues examined cellphone use while driving and explored possible associations with individual traits related to impulse control and reward sensitivity (using the Urgency Premeditation Perseverance Sensation Seeking Impulsive Behavior Scale, UPPS, Whiteside & Lynam, 2001). Likewise, Sanbonmatsu et. al (2013) asked participants to report how often they used their cellphones while driving, assessed a broader facet of technology engagement captured by the Media Multitasking Index (MMI, (Ophir, Nass, & Wagner, 2009)), and also examined trait impulsivity (Barratt Impulsiveness Scale Version 11, (Patton, Stanford, & Barratt, 1995)) and sensation seeking (Sensation Seeking Scale, (Zuckerman, Eysenck, & Eysenck, 1978)). In both studies, a positive relationship was found between the assessed technology habits and the individual trait questionnaires, suggesting the existence of a common psychological trait.

Preliminary Findings

Our lab has also previously pursued the question of what motivates smartphone usage (Wilmer & Chein, 2016). Specifically, we attempted to delineate the interrelationships between smartphone usage, intertemporal preference (delay of gratification), impulse control, and reward sensitivity. In so doing, we developed a survey instrument with a focus on smartphone usage. By combining different aspects of mobile technology use into a single scale, we were able to obtain a novel metric of individual differences in mobile technology usage. Importantly, this method of assessing technology habits proved to be positively correlated with another widely-used index of technology habits (the MMI), indicating a common underlying behavior. Our Mobile Technology Engagement (MTE) scale thus seemed to be an effective measure encapsulating the various ways in which people engage with mobile technology, with a specific focus on the type of behaviors that are typical of smartphone and other portable e-device usage. Using this instrument, we sought to determine if individuals who reported heavier mobile technology use also exhibited a differential tendency to delay gratification. We further explored the factors that might drive such a relationship by assessing individual differences in both impulse control and reward sensitivity to see if these variables mediated the relationship between technology engagement and intertemporal preference. Results indicated a significant relationship between MTE and intertemporal preference. Where Atchley & Warden (2012) had demonstrated similarities in the processes by which information and monetary prompts are valuated, and Hayashi et al., (2015) had linked delay tolerance with cellphone use while driving, our research provided evidence that broader aspects of mobile technology use are also related to general differences in intertemporal preference. Lastly, our analyses revealed that impulse control also positively correlated with MTE and acted as a significant mediator of the relationship between technology engagement and intertemporal preference (whereas reward sensitivity did not) (Figure 1). These results demonstrate a link between mobile technology usage and intertemporal preference, and suggest that impulse control could be the common underlying trait that connects them.

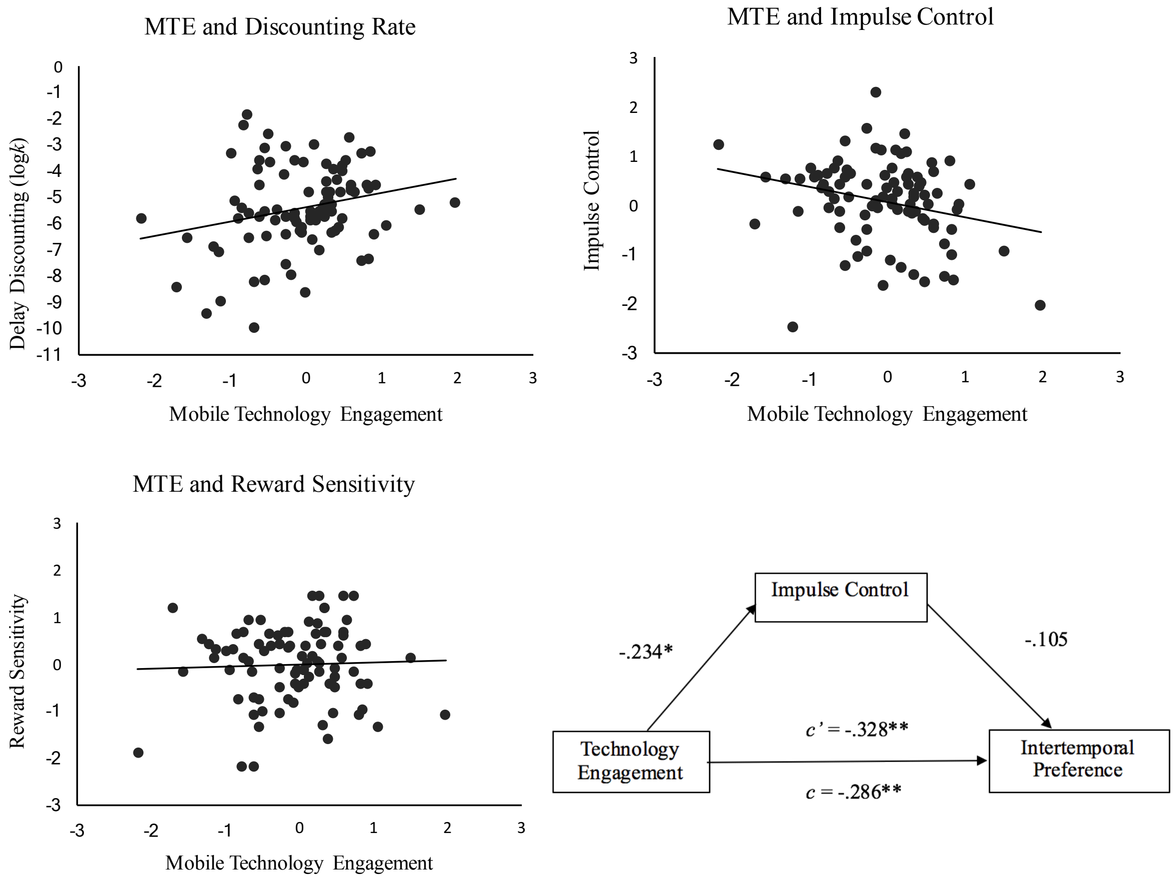

Figure 1. Results from Wilmer & Chein (2016). Top panel, from left to right: MTE scores are significantly positively correlated with discounting rate. MTE; MTE scores are negatively correlated with Impulse Control. Bottom panel, from left to right: No relationship between MTE scores and Reward Sensitivity; Impulse Control mediates the relationship between MTE scores and intertemporal preference. *Details on the mediation technique are outlined in the Results section.*

Neuroimaging Correlates of Technology Engagement and Intertemporal Preference

As discussed above, the past decade has seen a growing literature investigating the links between technology usage and cognitive and behavioral traits. Yet to date, there exists very little empirical evidence regarding the brain mechanisms by which these behaviors may be connected.

In one of the few studies directly exploring the links between technology habits and brain function, Moisala and colleagues (2016) demonstrated that heavy media multitaskers exhibited relatively poor performance on a sentence congruency task, and this behavioral deficit was associated with increased activity in the right prefrontal cortex. The authors suggested that heightened prefrontal engagement could be due to greater difficulty among heavy media multitaskers in recruiting cognitive control resources. Relatedly, Loh & Kanai (2014) found reduced gray matter in the anterior cingulate cortex of frequent media multitaskers, indicating that this habit may have a direct impact⇐direction? on the structural properties of an important locus of attentional control in the brain (though it should be noted that other functions have also been ascribed to this region (Shenhav, Cohen, & Botvinick, 2016).

Though not focused directly on technology-related behaviors, several recent studies have also explored brain-behavior associations in relation to intertemporal preference. In an early contribution, (McClure et al., 2004) demonstrated that functional networks underlying impulse control and reward processing contributed separately to selections of larger, later rewards versus a smaller, more immediate rewards. Subsequent work exploring the structural pathways connecting these networks reported correlations between individual differences in frontostriatal white matter and temporal discounting tendencies. Peper and colleagues (2013), for instance, showed that greater structural integrity in the connections between the entire striatum and the entire PFC was associated with decreased discounting of delayed rewards in a delay discounting task. Providing some further anatomical granularity, van den Bos and colleagues (2014) demonstrated that greater connectivity specifically between the mid-striatum and the dorsolateral prefrontal cortex (dlPFC) predicted less discounting of delayed rewards.

Recognizing important structural distinctions between ventral and dorsal sub-regions of the striatum, Hampton and colleagues (2017) hypothesized that these loci may also be unique in terms of their white matter connectivity to other brain regions, and in terms of their associations with delay discounting. Indeed, their results showed that within the left hemisphere, higher connectivity between the ventral striatum and the ventromedial prefrontal cortex (vmPFC) uniquely predicted steeper discounting on a delay discounting task, whereas connectivity between the dorsal striatum and vmPFC was not associated with discounting performance.

The neuroimaging evidence discussed above demonstrates that individual differences in white matter connectivity are related to inter-individual variation in intertemporal preference. Despite further evidence for an association between intertemporal preference and mobile technology use, to date, there have not been any published attempts to determine whether differences in white matter connectivity are also linked to differences in the ways in which individuals interact with technology. Given the distinct relationships that white matter connectivity and mobile technology engagement each possesses with regard to intertemporal preference, I aimed to extend the behavioral work undertaken in Study 1 by further investigating in Study 2 whether the white matter paths associated with delay discounting task performance are also implicated in a direct relationship with MTE.

Aims for the Current Research

Aim 1: Replicate and extend prior work, using an objective measure of smartphone use.

By using many of the same measures that were deployed in our prior study of smartphone habits, the current work served as an important opportunity to replicate previous findings. The crucial need for empirical replication in the field of psychology was recently highlighted by the Reproducibility Project (Open Science Collaboration, 2015; though see: Anderson et al., 2016; Gilbert, King, Pettigrew, & Wilson, 2016a, 2016b;)

However, an obvious shortcoming of our prior research (and the majority of empirical research conducted in this domain) was that the findings depended upon only self-reports of mobile technology habits (Wilmer & Chein, 2016). Until quite recently, there was no reliable way to monitor the usage of various apps on a smartphone, but the operating system that is now standard on all modern Apple iPhones (iOS 8 or above) includes a function that automatically tracks the time that a user spends with each individual application showing on the phone's display. Accordingly, in Study 1, I supplement the self-reported MTE metric that was collected in our previous research with this objective measure of smartphone usage.

Aim 2: Explore the interrelationships among alternate indices of technology habits

Research investigating the psychological correlates of technology habits has utilized various self-report measures. The iPhone function just described enabled a determination of the relationship between this objective measure and participants' self-reports of their own smartphone usage. I thus set out to explore not only how well actual smartphone usage correlates with the previously developed MTE questionnaire, but also the extent to which usage relates to other commonly deployed metrics, including the MMI and the Mobile Phone Problematic Usage Scale (MPPUS). In this way, Study 1 could provide crucial information regarding the interpretation of prior empirical findings based on self-reports of technology habits.

Aim 3: Identify structural connectivity correlates of variation in technology habits

In Study 2, I hoped to shed light on the specific neural mechanisms that are associated with the relationships uncovered in Wilmer & Chein 2016, and pursued further in Study 1 of this dissertation. In so doing, this work was intended to provide convergent evidence regarding the involvement of impulse control and reward sensitivity on the processes that guide deliberation in intertemporal choice, and that connect these processes to mobile technology habits. Though no prior research has investigated white matter correlates of technology usage, the analyses presented in this study were guided by a foundational literature researching the white matter correlates of intertemporal preference. As such, I sought to explore the possibility of a relationship between MTE scores and the brain's white matter connectivity within pathways that have been implicated in performance on a delay discounting task. Exploring these structural relationships allowed me to connect the current work to a small but informative literature about the basis of delay discounting and structural connectivity. Further, this technique allowed investigations into brain-behavior relationships that are specific to single task measures.

CHAPTER 2

STUDY 1: METHODS

Subjects

Participants were a sample of 110 Temple University students enrolled in undergraduate courses. Four participants were removed from the analyses for not properly following task instructions, leaving a final sample of 106 (69.8% female; age M = 20.1, SD = 2.48). The sample was racially diverse (67.9% self-identified as Caucasian or white, 13.2% as African-American or black, 10.4% as Asian, 5.7% as more than one race, and 2.8% declined to respond). All participants were least 18 years of age and were fluent in written and spoken English. All procedures were approved by the Institutional Review Board at Temple University. Participants were recruited through Temple University's SONA system and were given course credit for participation in this study.

Measures

Mobile Technology Engagement Scale.

Participants' engagement with mobile technology was determined, in part, using the Mobile Technology Engagement (MTE) scale (Wilmer & Chein, 2016). By assessing self-reported behaviors regarding different facets of mobile technology, the index characterizes broad smartphone engagement patterns, while not being too narrowly focused on a specific type of usage. The three topics that comprise this scale are: 1) phone-based social media use, 2) frequency of public status updating, and 3) phone-checking behavior. *Phone-based social media use* is determined by the participants' responses to four Likert-style questions about their daily usage of various mobile social media applications (Facebook, Twitter, Instagram, Snapchat). In the time between when the scale was first developed for Wilmer & Chein (2016) and the implementation of the current study, one social media app (Vine) we had included in our initial study went out of favor and eventually out of the market entirely. At the same time, a different app (Snapchat) became widely used, especially among the undergraduate cohort which constituted our study sample. Therefore, in the version of the MTE deployed for the current research, Snapchat usage was assessed in place of Vine usage. *Frequency of posting public status updates* was determined by the participants' response to a single Likert-style question, "How often do you post public status updates?" *Phone-checking behavior* was determined by the average of answers to three Likert-style questions: "How often do you check your phone for new activity?", "How often do you find yourself checking your phone when you have a few moments to spare?", and "How often do you find yourself checking your phone during conversations or when hanging around with friends?" Means of the z-scores from the three sub-categories were taken to form the MTE score for each participant.

Media Multiuse Questionnaire

I also gathered information regarding the participants' technology multitasking habits using the *Media Multitasking Index* (MMI) (Ophir et al., 2009). The MMI provides an estimate of the amount of time one spends multitasking with various forms of media. In the standard form, participants are asked to estimate the total number of hours they spend engaging in 12 different forms of media (e.g., watching television, playing video games, talking on the phone, instant messaging, etc.), and to specify, across a series of pages (one for each media type), the degree to which they use each media technology concurrently with each of the other media formats (i.e. engage in media multitasking).

The MMI score is an aggregated score based on the sum total of multitasking habits (specific calculation is described in Ophir et al., 2009). For expediency, I used a matrix-style version of the MMI, which allowed participants to detail their media multi-tasking habits on a single computerized form, rather than across a series of repeated forms pertaining to each media type.

Mobile Phone Problematic Usage Scale

The Mobile Phone Problematic Usage Scale (Bianchi & Phillips, 2005) was implemented as a third measure of mobile phone usage. This scale is meant to assess excessive or problematic mobile phone usage and is measured by a 27-item questionnaire. All questions are responded to on a 10-point Likert scale with 1 (not at all true) and 10 (very true). Scores on this questionnaire can range from 27 to 270.

Self-Reported Technology Habits Construct

Each of the three self-report measures discussed above probes technology-related habits in a disparate way. To assay participants' general tendency to engage in these behaviors, I also computed a construct level representation of technology habits based on the mean of the z-scores from each scale.

Actual Phone Usage

Where available, I also collected information provided via the iPhone OS detailing participant's actual weekly usage of the apps installed on their phones. This approach provided an objective account of phone usage that circumvented some limitations of self-report data. Furthermore, it allowed me to obtain data regarding the parallels between participants' perception of their own mobile technology usage and actual usage patterns. To compare participants' self-reports of the amount of time they spend on particular apps with the Actual Phone Usage, I computed average daily usage for each app by dividing the time spent on the app in over the past week by seven. From the sample of 106 participants, I successfully obtained Actual Phone Usage data from 56 individuals. My ability to obtain data from all participants was limited by incompatible operating systems, system updates performed within the last 7 days, and participants being unwilling to share their private data.

Intertemporal Preference

I assessed individual differences in the tendency to delay gratification in favor of larger, later, rewards using a Delay Discounting task (O'Brien, Albert, Chein, & Steinberg, 2011). In the Delay Discounting task, participants were asked to make hypothetical choices between a smaller sum of money offered now versus a larger sum of money (always $1000) offered at six different delays: one day, one week, one month, three months, six months, and one year. The smaller sum of money offered was varied systematically, until the participant reached an indifference point – the value at which the subjective value of the smaller immediate offer matched the subjective value of the larger ($1000) delayed offer (Ohmura, Takahashi, Kitamura, & Wehr, 2006). Participants completed 10 trials at each delay interval. Using this data, I calculated each individual's discount rate (k) as well as their indifference points at each delay. As is commonly done, I applied a natural log transformation to all k-values in order to reduce skewness to an acceptable level. Based on previous experience with this task (O'Brien et al., 2011; Weigard, Chein, Albert, Smith, & Steinberg, 2014; Wilmer & Chein, 2016) I expected the responses to the longer delays (six-month and one-year) to have the greatest individual subject variance. Thus, I averaged the longest delays and used them as a more sensitive index of individual variation in intertemporal preference.

Reward Sensitivity

Two instruments were used to create a Reward Sensitivity construct: a subset of questions from Zuckerman's revised *Impulsive Sensation Seeking* scale and a subscale of the *BIS/BAS* questionnaire. The *Impulsive Sensation Seeking* measure (Zuckerman et al., 1993) is a 19-item self-report questionnaire that intentionally conflates impulsive and sensation seeking behaviors in order to broadly characterize these personality traits. To isolate sensation seeking, Steinberg et al., 2008 identified a subset of 6 items from the updated Zuckerman scale that most purely related to this construct ("I like to have new and exciting experiences and sensations, even if they are a little frightening," "I like doing things just for the thrill of it," "I sometimes like to do things that are a little frightening," "I'll try anything once," "I sometimes do 'crazy' things just for fun," and "I like wild and uninhibited parties"). These items were answered as either true (coded 1) or false (coded 0), and item scores were averaged to create a mean Sensation Seeking score.

The *BIS/BAS* Scales are measures of behavioral inhibition and behavioral approach (Carver & White, 1994). For the purposes of the present study, I was primarily concerned with the behavioral approach component (BAS), which is itself comprised of three subscales: Fun Seeking, Reward Responsiveness, and Drive. Because I was specifically focused on targeting individual reward sensitivity, the Reward Responsiveness subscale were specifically utilized in my analyses.

In an attempt to extend upon the approach carried out in Wilmer & Chein (2016), I employed a behavioral measure of reward sensitivity, the Monetary Incentive Delay task (Knutson, Westdorp, Kaiser, & Hommer, 2000). In order to win or avoid losing the amount of money shown, participants were instructed to respond as quickly as possible by pressing a button whenever the target stimulus (a white square) appeared. Each target was preceded, with variable delays, by a cue screen indicating the specific monetary value that could be won or lost on the trial. The variant involved four trial types: 1) win $1.00, 2) win $0.10, 3) lose $0.50, and 4) no gain/loss. Analyzing differences in reaction times across the various conditions has been previously used as a measure of reward sensitivity (Helfinstein et al., 2013). Following this model, I treated the difference in reaction times for potential win trials versus that for no gain/loss trials as a behavioral index of reward sensitivity. However, in analyzing these results, I was unable to discern any significant differences among the reaction times across the four trial types. Thus, I did not include a behavioral measure of reward sensitivity, and the construct presented in the current research is identical to that which was presented in Wilmer & Chein (2016).

Impulse Control

To pursue the efforts of the replication, an Impulse Control construct was calculated by taking the average score from two measures, the *Barratt Impulsiveness Scale* and the false alarm rate on a Go/NoGo task as was done in Wilmer & Chein (2016). *Barratt Impulsiveness Scale* is a widely used self-report measure of impulsivity (Patton et al., 1995). Again, based on the findings of Steinberg et al., 2008, I used only 18 items of the full 30-item questionnaire having specificity with respect to impulsive behavior (rather than sensation seeking). Each item was answered on a 4-point scale (*rarely/never, occasionally, often, almost always*) and scores were averaged, with higher scores indicative of greater impulsivity.

The Go/NoGo task used in the current study involves the rapid presentation of a series of Go ("x") and NoGo ("k") stimuli. Participants were instructed to produce a button press response following each "x", but to withhold responding whenever they saw a "k" stimulus. The stimuli were presented for 250ms each, followed by an unpredictable ITI ranging between 750ms and 1750ms. In total, 333 stimuli were presented, of which 50 were NoGo trials (k's). The NoGo trials were pseudo-randomly interspersed into the series such that a NoGo trial is equally often preceded by 1-10 prior Go trials (5 occurrences of each). False alarms were recorded each time a participant responded on a trial in which a "k" was shown. The entire task lasted just over 8.5 minutes. Normalized scores from both the *Barratt Impulsiveness Scale* and Go/NoGo measures were inverted so as to reflect impulse control rather than impulsivity (i.e. a higher score on the construct indicated a stronger tendency to control impulsive responses).

Procedure

Upon arrival to the experiment room, each subject was given a basic orientation to participation in the study, and was asked to sign consent forms which explained the study in detail. The experimenter then asked the participant for his or her phone, which was held outside of the experiment room in silent mode, such that no tones or vibrations would cause a distraction to the participant. The study commenced with participants completing an initial set of questionnaires, which included the MTE, the MMI, the MPPUS, the *Impulsive Sensation Seeking* scale, the *Barrett Impulsiveness Scale*, and the *BIS/BAS questionnaire*. If the participant possessed a phone (and recent iOS version) that collected objective usage data, the experimenter affirmed the participant's permission to use the phone to determine app-specific usage during the week leading up to the session.

While the experimenter recorded the usage data, the participant was engaged in the series of computer-based behavior tasks: Go/NoGo, Delay Discounting, and Monetary Incentive Delay.

CHAPTER 3

STUDY 1: RESULTS

Relationship Among Measures of Technology Engagement

Basic descriptive statistics for each measure are provided in Table 1. Following the approach of Wilmer & Chein (2016), I explored the relationships between MTE scores and other established measures of technology usage. To do this, I examined the bivariate correlations between normalized scores for the MTE and each of the two additional scales we had used: the MMI, and MPPUS. This analysis revealed a significant positive correlation between the MTE and the MMI (r = .381, p < .001), as well as the MPPUS (r = .352, p < .001). I observed a trend-level, and non-significant, correlation between the MMI and the MPPUS (r = .182, p = .067).

In the subset of participants from whom I was also able to gather Actual Phone Usage (n = 57), I observed a further significant relationship between their scores on the MTE and the total amount of time spent on their phones over the prior seven days (r = .332, p = .012). Actual Phone Usage was not, however, at all correlated with either MMI scores (r = .028, p = .844) or MPPUS scores (r = .057, p = .675). Given these data, I was able to establish that among self-report indices, only the MTE provided a generalizable metric of participants' actual engagement with their mobile phones.

Table 1
Descriptive statistics for individual measures

		Minimum	Maximum	Mean	Std. Deviation
	Actual Phone Usage	598	2852	1448.53	524.46
	MMI	0.75	7.22	3.56	1.5
	MPPUS	31	175	86.81	28.11
MTE	Phone-based social media use	5	29	17.51	5.19
	Frequency of posting public status updates	1	7	2.33	1.2
	Phone-checking behavior	-2.28	1.55	0	0.7
Intertemporal Preference	Mean indifference point	1	999	572.57	275.98
Impulse Control	Go/NoGo false alarms	1	40	19.32	8.24
	Barratt Impulsiveness Scale	1.39	3.33	1.97	0.36
Reward Sensitivity	Zuckerman's Impulsive Sensation Seeking scale	0	1	0.57	0.31
	BAS-reward	12	20	16.6	1.89

Relationships Among Mobile Technology Usage Measures and Psychological Traits

A primary objective of the current research was to determine if the findings in Wilmer & Chein (2016) would be replicated. To determine this, I analyzed the correlations between the participants' self-reported assessment of their own mobile technology usage and each of the cognitive constructs outlined above. Similar to the findings reported in Wilmer & Chein (2016), I found a significant correlation between MTE scores and mean indifference point for the long (6-month and 1-year) delays (r = -.194, p = .047) probed in the delay discounting task. However, there was not a significant correlation between MTE and participants' average discounting rate (log$k$) (r = .12, p = .224), a correlation that had also been significant in Wilmer & Chein (2016).

As discussed above, the findings presented in Wilmer & Chein (2016) indicated a significant negative relationship between impulse control and MTE, and the absence of a relationship between reward sensitivity and MTE. In the current study, a different pattern emerged: reward sensitivity was significantly positively correlated with MTE (r = .359, p < .001), whereas there was no evidence of a relationship between MTE and impulse control at the construct level (r = -.039, p = .691). Analyzing the individual components of the impulse control construct (reverse-coded here to reflect impulse control, rather than impulsivity) revealed a negative non-significant correlation between MTE and Barratt's Impulsivity scores (r = -.176, p = .071), whereas the Go/NoGo false alarms bore a somewhat positive, non-significant relationship to MTE (r = .121, p = .218). The relationships between MTE and each cognitive trait we examined are shown in Figure 2.

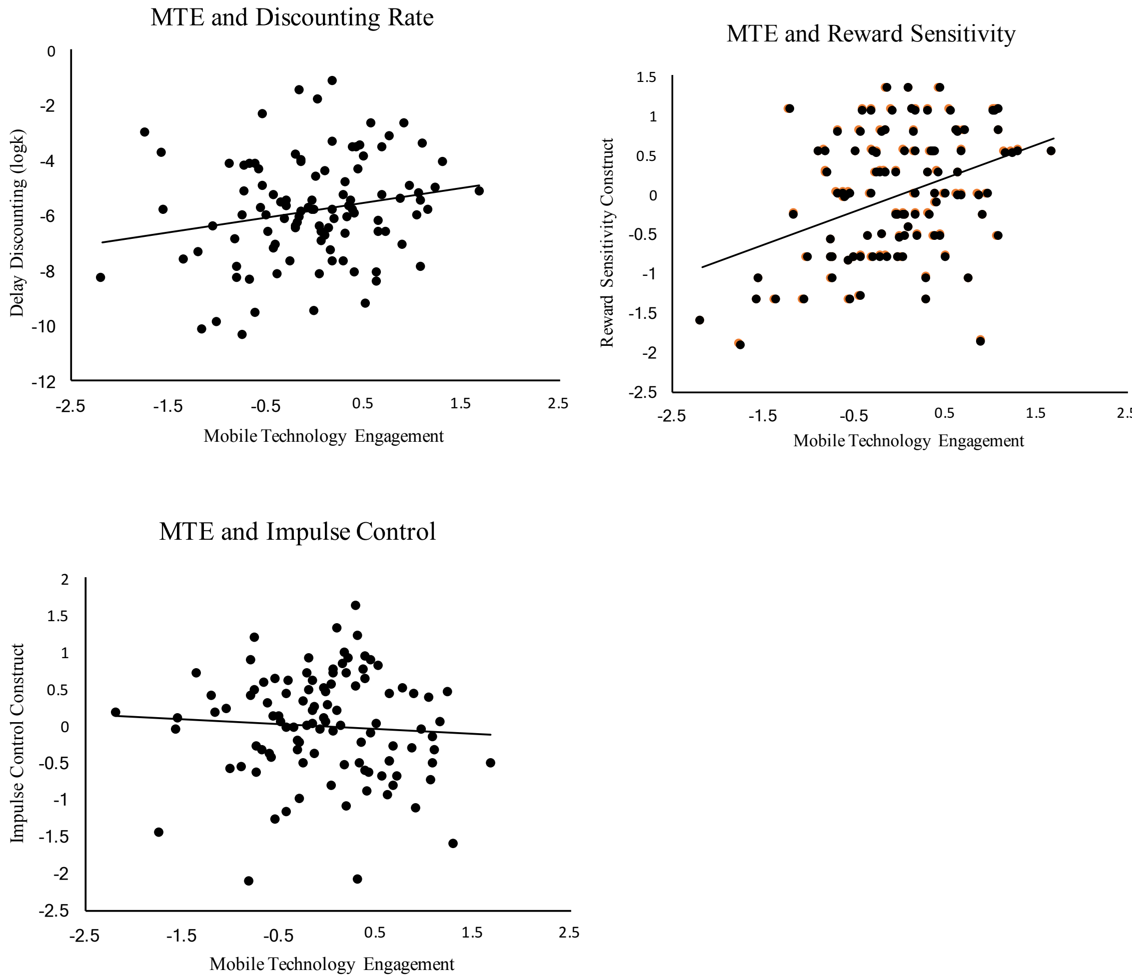

Figure 2. Results of the replication attempt from the current research. Top panel from left to right: MTE is negatively correlated with indifference points at 6-month and 1-year delays; MTE is positively correlated with Reward Sensitivity. Bottom panel: No relationship between MTE and Impulse Control

Analyzing how the self-reported data from the MMI and MPPUS were associated with cognitive functions also led to some intriguing findings. While neither the MMI nor MPPUS was significantly correlated with delay discounting performance, each scale had disparate patterns of relationships with impulse control and reward sensitivity. For the MMI, there was a significant negative correlation with impulse control (r = -.211, p = .033), but no relationship with reward sensitivity (r = .110, p = .272). Meanwhile, MPPUS scores exhibited the reverse pattern of correlation, with a positive relationship with reward sensitivity (*r* = .203, *p* = .037), but no relationship to impulse control (*r* = .125, *p* = .201).

In an effort to assay the tendency to engage in technology-related behaviors in a more general approach, I combined the three scales (MTE, MMI, and MPPUS) into a single Technology Habits Construct to analyze its pattern of relationships with each of the psychological constructs. This combined measure was significantly positively correlated with reward sensitivity (*r* = .315, *p* = .001) and trended toward a negative relationship with impulse control (*r* = -.167, *p* = .087). The construct, however, was not related to intertemporal preference as assessed by either log*k* (*r* = .068, *p* = .489) or indifference points at the longest delays (*r* = -.108, *p* = .271).

Correlations of Sub-Components of the MTE

The use of an aggregate MTE variable in the present study was motivated by the findings presented in Wilmer & Chein (2016). In the current research, I was also interested in exploring which specific components of the aggregated variable were driving the relationships I observed. Separate examination of the three components of the MTE scale revealed relationships with each of the individual differences measures that were assessed. Individual differences in intertemporal preference were significantly correlated with frequency of posting public status updates (*r* = -.226, *p* = .020), but not with checking habits (*r* = -.126, *p* = .201) or time spent on social media (*r* = -.085, *p* = .388). All three subcomponents were found to be positively correlated with reward sensitivity (Checking habits: *r* = .216, *p* = .026; Social Media: *r* = .290, *p* = .003; Status Updates: *r* = .268, *p* = .006). None of the subcomponents were significantly correlated with differences in impulse control (Checking habits: $r = -.070$, $p = .477$; Social Media: $r = -.070$, $p = .474$; Status Updates: $r = .056$, $p = .569$).

Breaking down the MTE scale into its subcomponents also revealed associations with the various other methods of assessing technology usage. I found that self-reported frequency of checking one's phone was positively associated with the MMI ($r = .311$, $p = .001$) and the MPPUS ($r = .356$, $p < .001$), but not with the objectively assessed Actual Phone Usage ($r = .124$, $p = .358$). In contrast, frequency of posting public status updates was correlated with total Actual Phone Usage ($r = .392$, $p = .003$), but not with either the MMI ($r = .122$, $p = .221$) or the MPPUS ($r = .111$, $p = .256$). Time spent using social media apps was significantly correlated with the MMI ($r = .386$, $p < .001$) and the MPPUS ($r = .292$, $p = .002$), but was not associated with Actual Phone Usage ($r = .185$, $p = .169$).

To illustrate the myriad relationships among this array of variables, I produced two correlation tables. The first (Table 2) shows the how each of the construct variables relate to each other. The second (Table 3) provides a more granular look at individual components that comprise each of the construct variables.

Table 2

Correlations among construct variables

	MTE	MMI	MPPUS	Discounting	Impulse Control	Reward Sensitivity
Actual Usage	**0.342**	0.028	0.057	**-0.288**	0.065	0.061
MTE		**0.381**	**0.352**	**-0.202**	-0.039	**0.359**
MMI			0.182	-0.036	**-0.211**	0.110
MPPUS				-0.029	-0.125	**0.203**
Discounting					0.112	0.029
Impulse Control						-0.127
Reward Sensitivity						

Note: Bold numbers represent relationships where p < .05. Red panels indicate positive relationships, whereas blue panels indicate negative relationships. Discounting represents the mean of the indifference point at 6 months and 1 year delay periods.

Table 3

Correlations among components of construct variables

		Mobile Technology Engagement			MMI	MPPUS	ITP	Impulse Control		Reward Sensitivity	
		SM Use	Updates	Checking	Full Scale	Full Scale	DD	GNG FAs*	Barratt's*	SS	BAS
	Actual Usage	0.185	**0.345**	0.124	0.028	0.057	**-0.288**	0.041	0.056	-0.075	0.115
Mobile Technology Engagement	SM Use		**0.327**	**0.277**	**0.386**	**0.292**	-0.085	0.011	-0.111	0.178	**0.242**
	Updates			0.138	0.123	0.072	**-0.201**	**0.232**	-0.186	0.147	**0.197**
	Checking				**0.311**	**0.356**	-0.126	0.014	-0.113	0.150	0.166
	MMI					0.182	-0.036	**-0.219**	-0.087	0.095	0.082
	MPPUS						-0.029	0.031	**-0.209**	0.141	0.170
ITP	Discounting							0.016	0.144	-0.024	0.060
Impulse Control	Go/No-Go FAs*								0.006	0.113	0.047
	Barratt's*									**-0.396**	-0.136
Reward Sensitivity	Zuckerman's SS										0.173
	BAS - Reward										

Note: Bold numbers represent relationships where p < .05.
**These measures are reverse coded to represent impulse control rather than impulsiveness. Red panels indicate positive relationships, whereas blue panels indicate negative relationships. Discounting represents the mean of the indifference point at 6 months and 1 year delay periods.*

Mediation Analyses of MTE and Intertemporal Preference

Wilmer and Chein (2016) used a mediation technique to reveal a significant mediation effect for impulse control, but not reward sensitivity, in the relationship between MTE and intertemporal preference (*Figure 1)*. In an attempt to determine whether the present data might replicate this aspect of previous findings, I again examined whether impulse control and/or reward sensitivity mediated the relationship between intertemporal preference and technology engagement with the new sample of participants. To test this possibility, I conducted mediation analyses using the bootstrapping methods delineated by Preacher and Hayes (2004) and utilizing Hayes's PROCESS Model (Hayes, 2013; Preacher & Hayes, 2004). Each analysis was performed using 10,000 bootstrap resamples to estimate the indirect effect of the proposed mediator variables. The bootstrapping method yields 95% confidence intervals (CIs) for each proposed mediator and its indirect effect. If zero is not included within an estimated 95% CI, the indirect effect is taken to be significantly different from zero. The indirect effect of MTE through impulse control yielded a bootstrapped CI that included zero (b = .023, 95% CI [-.0471, .2012]), indicating that impulse control is not a significant mediator in the relationship in the current data. The indirect effect of MTE through reward sensitivity similarly yielded a non-significant result (b = .001, 95% CI [-.2426, .2035]).

Relationships Between Actual Phone Usage and Cognitive Traits

To further explore our findings, I analyzed the correlations between the Actual Phone Usage metrics and each of the cognitive constructs outlined above. It is important to note that I could only conduct these analyses in the sub-sample (n = 56) from whom I was able to gather actual usage data. In the analysis of intertemporal preference, I found a significant correlation between Actual Phone Usage and the average indifference point at long delays (r = -.288, p = .031). Moreover, this relationship remained significant even when including the shorter time points in the calculation of average indifference point (r = -.277, p = .038). The correlation between Actual Phone Usage and discounting rate (log$k$) was marginally significant (r = .260, p = .053).

I did not observe a significant relationship between total time spent on one's phone and either the construct variable for impulse control (r = .065, p = .630) or reward sensitivity (r = .061, p =.653).

Accuracy of Participants' Self-Reported App Usage

An additional advantage conferred by having an objective measure for the actual amount of time participants spent on their phones was the ability to assess the correspondence between subjective (self-reported) beliefs and Actual Phone Usage. Specifically, I compared participants' objective usage to their claims (on the MTE) regarding the amount of time they typically spend using the following social media apps: Facebook, Twitter, Instagram, and Snapchat. The results are outlined in the Tables 4-7.

Table 4

Participants actual time spent using Facebook per day, categorized by their self-reported estimates of daily Facebook usage

	n	Mean	Minimum	Maximum	Std. Deviation
Rarely ever use	5	5.83	1.14	15.43	5.79
5-10 minutes	5	13.2	6	30.86	10.3
10-20 minutes	16	24.23	4.86	66	17.53
20-40 minutes	5	41.14	16.29	62.57	18.34
40-60 minutes	5	53.66	17.14	104.57	33.03
Over an hour per day	2	109.71	95.14	124.29	20.61
Total	38	30.95	1.14	124.29	29.53

Table 5

Participants actual time spent using Twitter per day, categorized by their self-reported estimates of daily Twitter usage

	n	Mean	Minimum	Maximum	Std. Deviation
Rarely ever use	2	6.5	2.71	10.29	5.35
5-10 minutes	6	10.52	4.29	20.57	6.32
10-20 minutes	8	16.79	3.14	24	8.59
20-40 minutes	8	22.61	12.86	33.43	7.33
40-60 minutes	5	35.31	17.14	66	18.45
Over an hour per day	4	46.29	22.29	99.43	35.88
Total	33	22.82	2.71	99.43	18.59

Table 6

Participants actual time spent using Instagram per day, categorized by their self-reported estimates of daily Instagram usage

	n	Mean	Minimum	Maximum	Std. Deviation
Rarely ever use	1	2.57	2.57	2.57	-
5-10 minutes	3	12.19	6.57	17.14	5.38
10-20 minutes	9	27.63	5.29	89.14	24.39
20-40 minutes	24	23.94	5	46.29	12.19
40-60 minutes	8	39.48	6.43	70.29	18.28
Over an hour per day	5	49.37	19.71	125.14	42.94
Total	50	28.5	2.57	125.14	21.7

Table 7

Participants actual time spent using Snapchat per day, categorized by their self-reported estimates of daily Snapchat usage

	n	Mean	Minimum	Maximum	Std. Deviation
Rarely ever use	2	20.14	6.86	33.43	18.79
5-10 minutes	6	23.14	10.29	42	12.57
10-20 minutes	12	17.58	4.57	46.29	13.93
20-40 minutes	13	27.49	10.29	48.86	12.65
40-60 minutes	9	38.59	5.29	90.86	24.74
Over an hour per day	8	38	7.43	95.14	28.29
Total	50	27.98	4.57	95.14	19.73

CHAPTER 4

STUDY 1: DISCUSSION

By successfully replicating the significant positive relationship between MTE and performance on the delay discounting task, the results of the current research provide additional corroboration of the finding from Wilmer & Chein (2016) that engagement with mobile technology is related to intertemporal preference. The small effect size observed in the current research (r = -.202) is consistent with the relationship observed in Wilmer & Chein (2016) (r = -.286). However, I did not replicate the significant relationship previously observed between MTE scores and Impulse Control, and instead found a significant relationship between MTE and Reward Sensitivity. Analyzing the individual components of the Impulse Control construct revealed an effect size for the *Barratt Impulsiveness Scale* (r = -.176) that was similar to the relationship between MTE and Impulse Control as observed in Wilmer & Chein (2016) (r = -.234). This suggests that the lack of a relationship between MTE and Impulse Control in the current dataset was due to the lack of a relationship between MTE and performance on the Go/NoGo task.

Though the evidence presented does not suggest a causal directionality, it is nonetheless important for people to understand this link between mobile technology engagement and intertemporal preference. A tendency to be unwilling to wait for rewards can be a potentially dangerous trait that has been linked to drug abuse and gambling addictions (for reviews, see: Bickel & Marsch, 2001; Reynolds, 2006). If overusing one's mobile phone has the power to exacerbate this trait, then it is important for people to be cognizant of their own usage. On the other hand, if being endowed with the natural tendency to seek immediate gratification is causing certain individuals to overuse their phones, it is similarly important for these individuals to understand that they are especially at risk of being susceptible to the draw of mobile technology devices.

In Wilmer & Chein (2016), we emphasized the differential aspects of reward sensitivity and impulse control that each contribute to the decisions one makes in the delay discounting task. In that paper, we reported results indicating that impulse control was significantly associated with MTE scores. Further, we demonstrated that an impulse control construct was a significant mediator of the relationship between technology engagement and intertemporal preference. The data from that study did not indicate a significant relationship between reward sensitivity and technology engagement – a relationship that had been observed in other prior research (Pearson et al., 2013; Sanbonmatsu et al., 2013). In our discussion, we posed the question: "What drives people to engage with their smartphones?" We concluded that the evidence from our research had indicated that technology habits were driven more strongly by uncontrolled impulses rather than by the desire to pursue rewards. The data from Study 1 more closely align with the observations of Pearson et al. (2013) and Sanbonmatsu et al. (2013), in that MTE scores were correlated with reward sensitivity.

This discrepancy in the data from two similar samples inspired me to further analyze which aspects of the MTE were driving the relationships among intertemporal preference, impulse control, and reward sensitivity. Because the MTE is a construct of three unique smartphone related behaviors (frequency of checking one's phone, time spent on social media apps, and frequency of posting public status updates), I thought it logical to examine each behavior independently and to explore the relationships each held with relevant cognitive functions. In the current dataset, none of these subcomponents were at all related to the impulse control construct. Conversely, all three subcomponents were significantly correlated with reward sensitivity.

In Wilmer & Chein (2016), we demonstrated that the Mobile Technology Engagement scale was significantly positively correlated with another commonly implemented metric of technology usage patterns, the MMI. By replicating this finding, the current research further demonstrates that patterns of engagement with technology can be fairly robustly assessed with alternative measures. This study also extends that finding by showing a significant correlational relationship between the MTE and the MPPUS. A more nuanced examination of how each measure (and the MTE sub-scales) relate to specific cognitive traits, however, demonstrates that each measure is differentially sensitive to the factors that drive aspects of technology engagement, and may thus have more apt uses depending on the specific research question under consideration.

Analyses also revealed that participants' MTE scores were significantly correlated with the total amount of time they spent on their phones, as assessed by an objective and non-intrusive measure. Accordingly, the results suggest that the MTE successfully condenses aspects of usage that are assessed by other scales into a single measure that is able to capture the underlying behavior in a coarse enough approach that it better captures relationships to specific cognitive traits. While gathering data objectively yields a more accurate index of phone use patterns, doing so is time-consuming for the experimenter and also restricted, based on the type of phone each participant owns and the willingness of the participants to share their private usage data. Moreover, the MTE assesses participants' tendencies to post public status updates, which cannot be gleaned from the Actual Usage Data.

CHAPTER 5

STUDY 2: METHODS

Study 2 combined behavioral and self-report assessments with diffusion imaging of participants' white matter pathways, collected via an MRI scanner located at Temple University Hospital. This study provided empirical support for the hypotheses under Aim 3. Additionally, because several of the measures overlapped with those included in Study 1, this study provided supplemental data that could be applied to Aim 1.

Subjects

Participants were 20 undergraduate students recruited from Temple University. Two individuals did not return their questionnaires; therefore, I could not use their data for any of the analyses I wanted to perform and they were removed from the sample. One participant was removed from the sample because of an error recording the diffusion sequence. Finally, one participant was removed from all analyses involving the delay discounting task for failure to follow instructions. The final sample size for the analyses presented below consisted of 16 participants (70.6% female; age M = 20.23 years, SD = .90). Due to the small sample size, the data presented in Study 2 should be considered preliminary. I plan to recruit additional participants to reach our final desired sample size. The sample was racially diverse (41.2% self-identified as Caucasian or white, 23.5% as Asian, 17.6% as African American or black, 11.8% as more than one race). All participants were over 18 years of age and fluent in written and spoken English. Participants were recruited through Temple University's SONA system and were compensated $30 in addition to bonuses based on their performance on the tasks completed in the scanner.

Measures

Mobile Technology Engagement

Participants in this study completed the MTE as described above in Study 1. This portion of the study was conducted before the participants entered the scanner.

Intertemporal Preference

Participants completed the Delay Discounting task, as described in Study 1. This portion of the study was conducted before the participants entered the scanner.

Reward Sensitivity

Participants completed the Zuckerman's *Impulsive Sensation Seeking* questionnaire and the Reward Responsiveness component of the *BIS/BAS* scale before entering the scanner.

Image Acquisition

Participants performed portions of the study in a 3T Siemens Magnetom Verio syngo MR B17 scanner located within Temple University Hospital. The scanning session began with a 30-slice T1-weighted anatomical localization sequence (1.1 X 1.0 X 7.0 mm). I collected diffusion weighted images (DWI) using a diffusion-weighted echo-planar imaging (EPI) sequence that covered the entire brain with the following imaging parameters: thirty-five 4.0 mm, contiguous oblique-axial slices were obtained every 2 s with each voxel having an in-plane resolution of 3.7 X 3.7 X 4.0 mm (Repetition Time (TR) = 2 s; Echo Time (TE) = 20 ms; flip angle = 70 deg). Additionally, I acquired a high resolution T1 weighted structural image using a standard MPRAGE acquisition sequence (9 minutes).

Selection of regions of interest

The findings from Hampton et al. (2016) provided the foundational basis for the investigation of the relationship between white matter connectivity and mobile technology engagement. Accordingly, I followed a similar methodology for the process of selecting regions of interest and for performing the DWI pre-processing and analysis. The FSL Oxford-Imanova Probabilistic Connectivity Striatal Atlas was used to derive lateralized masks for the seed region, the ventral striatum. Further, the sensorimotor and executive regions were subtracted as defined in the atlas, leaving only the most ventral (limbic) portion for the analyses. For the dlPFC, I used the cluster masks for Brodmann's areas 46 and 9 and constructed lateralized masks as defined by the Sallet Dorsal Frontal Connectivity Atlas. The vmPFC was defined using a normalized region of interest (ROI) as was originally detailed by Bartra et al. (2013), and lateralized ROIs were acquired by subtracting a mask of the contralateral hemisphere from each side.

All pre-processing was performed using FSL (Smith et al., 2004). In order to investigate specific white matter pathways, it was necessary to utilize "seeded" tractography, using the ventral striatum as the seed region. This seed provided a point from which the white matter that reaches the target ROIs originated. All tractography analyses were performed in the subjects' native space, and results were output in Montreal Neurological Institute (MNI) standard space. The FDT Toolbox was utilized to conduct probabilistic tractography, using a partial volume model and up to two fiber directions in each voxel. All of probabilistic tractography was conducted for each hemisphere alone, by using an exclusion mask to isolate it from the contralateral side.

From this method, I acquired the number of "streamlines" (probabilistic connections) that exist between the seed and each target ROI. To correct for inter-individual variability in the size of each ROI, I divided the number of afferent streamlines by the total non-voxels in the native space seed region, and divided the number of efferent streamlines by the number of non-zero voxels in the native space target region. The mean of these two values were calculated to produce a composite measure of connectivity between the seed and each target ROI. Example images of the vSTR-vmPFC (Figure 3) and vSTR-dlPFC (Figure 4) are shown below.

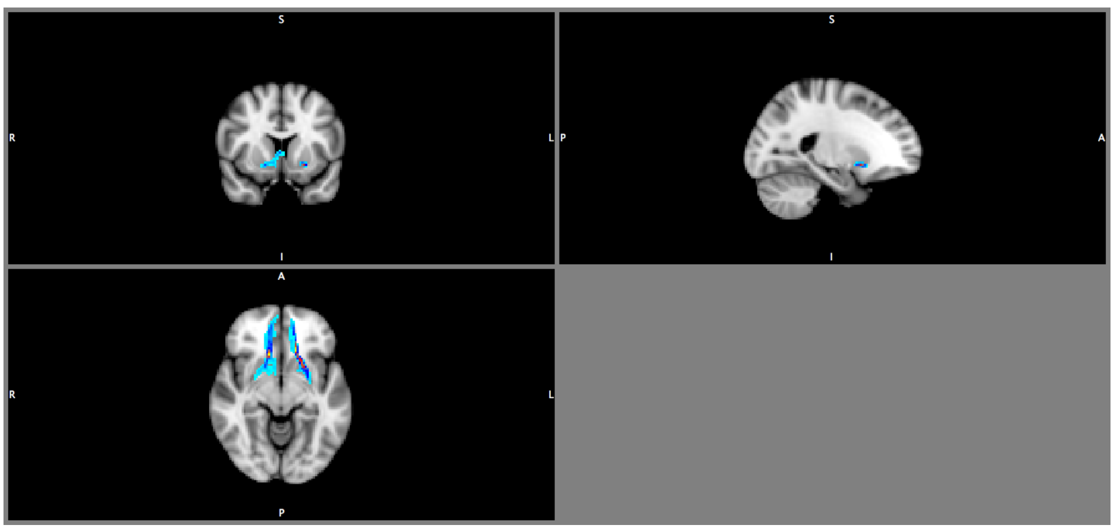
Figure 3. vSTR-vmPFC connectivity from a single participant.

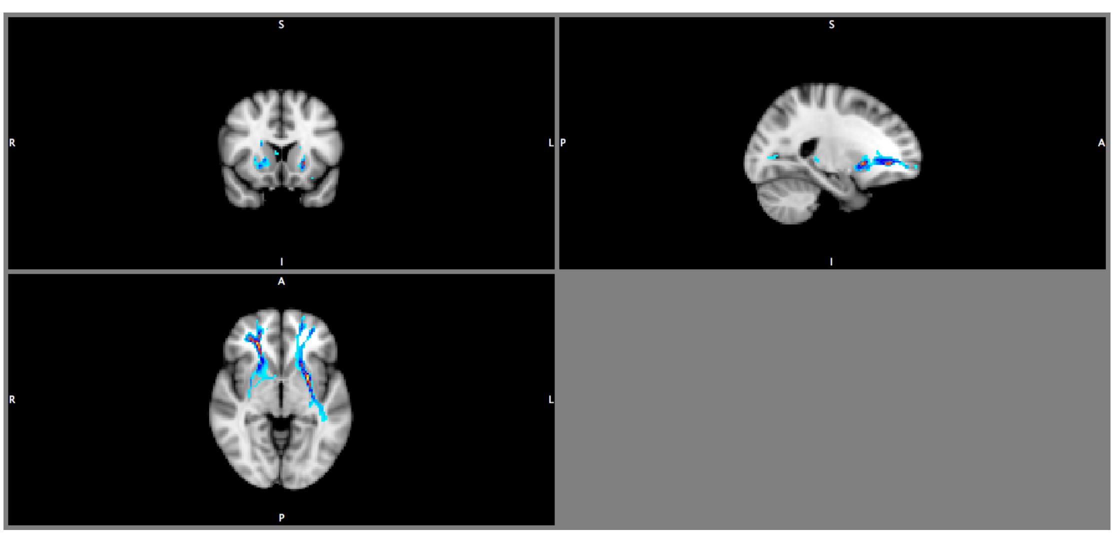
Figure 4. vSTR-dlPFC connectivity from a single participant.

CHAPTER 6

STUDY 2: RESULTS

Behavioral Results

The dataset I gathered in Study 2 included the same measures of intertemporal preference and MTE that were collected as part of Study 1. Having these data for an independent sample of individuals (albeit recruited from the same population of Temple University undergraduates) allowed me to conduct the same analyses to provide further confidence in the association between these two variables. Indeed, the results from this sample again revealed a significant correlation between MTE scores and a tendency to take the smaller, immediate reward rather than wait for a larger reward at the longest time points (6-months and 1-year) (r = -.658, p = .006). This sample, despite being much smaller, also demonstrated a correlation between MTE and discounting rate (log$k$) (r = .593, p = .015). These data again provide corroboration that greater technology engagement is associated with a greater willingness to accept smaller, more immediate rewards rather than waiting for larger rewards. However, despite a similar magnitude correlation for the relationship between MTE and Reward Sensitivity as was observed in Study 1 (r = .371, p = .142), this correlation did not reach significance in this small sample. The results from this sample did not indicate any relationship between MTE and impulse control (r = -.012, p = .964).

As I did for the Study 1 results, I produced two correlation tables to illustrate the relationships among the array of variables for the behavioral results of Study 2. The first (Table 8) shows the how each of the construct variables relate. The second (Table 9) provides a more granular look at individual components that make up the construct variables.

Table 8

Study 2: Correlations among construct variables

	Discounting	Impulse Control	Reward Sensitivity
MTE	**-0.658**	-0.012	**0.371**
Discounting		0.307	0.029
Impulse Control			-0.218
Reward Sensitivity			

Note: Bold numbers represent relationships where p < .05. Red panels indicate positive relationships, whereas blue panels indicate negative relationships. Discounting represents the mean of the indifference point at 6 months and 1 year delay periods.

Table 9

Study 2: Correlations among components of construct variables

		Mobile Technology Engagement			ITP	Impulse Control		Reward Sensitivity	
		SM Use	Updates	Checking	DD	GNG FAs*	Barratt's*	SS	BAS
Mobile Technology Engagement	SM Use		**0.749**	0.307	**-0.587**	0.022	-0.263	0.199	0.392
	Updates			**0.510**	**-0.558**	**0.37**	-0.250	0.167	0.25
	Checking				-0.491	0.312	-0.234	0.198	0.378
ITP	Discounting					0.092	0.465	-0.146	-0.350
Impulse Control	Go/No-Go FAs*						**0.517**	-0.404	-0.080
	Barratt's*							-0.287	-0.149
Reward Sensitivity	Zuckerman's SS								**0.697**
	BAS - Reward								

Note: Bold numbers represent relationships where p < .05. Red panels indicate positive relationships, whereas blue panels indicate negative relationships. Discounting represents the mean of the indifference point at 6 months and 1 year delay periods.

Neuroimaging and Behavioral Correlates

Regression models were constructed to analyze the relationships between the various white matter tracts and the two behaviors of interest: MTE and discounting rate. Left and right lateralized tracts were entered simultaneously as predictors, and age and gender were included as controls in each regression model.

Using the ventral striatum as a seed and the vmPFC as a target ROI, analyses revealed a significant regression model fit for discounting rate (log*k*) as it related to the number of probabilistic connections in this pathway ($F(4,11)=3.457$, $p = .046$, adjusted $R^2= .438$). Within this model, sex was the only regressor to independently account for a significant amount of variance (right: $\beta = 1.193E-6$ $t(11) = .250$, $p = .807$; left: $\beta = -2.287E-6$ $t(11) = -.979$, $p = .349$; age: $\beta = -.001$ $t(11) = -2.121$, $p = .057$; sex: $\beta = -1.011$ $t(11) = -2.266$, $p = .045$).

A regression model in the same pathway predicting MTE scores was also found to be significant ($F(4,12) = 4.112$, $p = .025$, adjusted $R^2 = .438$). Within this model, both lateralized tracts trended toward significance, though in opposite directions (right: $\beta = 8.247E-6$ $t(12) = 2.052$, $p = .063$; left: $\beta = -4.094E-6$ $t(12) = 2.126$, $p = .055$). These results indicate that MTE scores are associated with a relatively higher number of probabilistic connections in the vSTR-vmPFC in the right hemisphere, whereas they predict a relatively lower number in the same pathway in the left hemisphere. Neither age nor sex independently accounted for a significant amount of variance within the model (age: $\beta = .000$ $t(12) = -.585$, $p = .569$; sex: $\beta = -.637$ $t(12) = -1.741$, $p = .107$).

Examining connectivity from the vSTR to the dlPFC also produced a significant regression model predicting log*k* ($F(4,11) = 4.691$, $p = .019$, adjusted $R^2 = .496$). The individual regressors within this model did not independently account for a significant amount of variance (right dlPFC: $\beta = -1.586E-5$ $t(11) = -1.472$, $p = .169$; left dlPFC: $\beta = -3.395E-6$ $t(11) = -3.29$, $p = .759$; age: $\beta = -.001$ $t(11) = -1.362$, $p = .200$; sex: $\beta = -.726$ $t(11) = -1.922$, $p = .081$). The regression model examining vSTR-dlPFC connectivity did not reveal a significant effect predicting MTE ($F(4,12) = 1.403$, $p = .291$, adjusted $R^2 = .092$).

CHAPTER 7

STUDY 2: DISCUSSION

The findings presented in Study 2 should be interpreted cautiously due to the small sample size, which precludes firm conclusions based on the observed effects, be they significant or null-results. However, analyzing the trends found in this dataset can provide corroboration of the behavioral outcomes attained in Study 1 and can guide future research on the links between the brain and technology-related behaviors.

The behavioral results from this study provided further evidence of the relationship between intertemporal preference and engagement with mobile technology. In this sample, the phenomenon was demonstrated both by indifference points at the longest delays and by discounting rate. Similar to what was observed in Study 1, and standing in contrast to the observations made in Wilmer & Chein (2016), reward sensitivity seems to be more associated with mobile technology engagement than is impulse control. Though the correlation between MTE and reward sensitivity presented in the results of Study 2 did not reach significance, the magnitude of the correlation (r = .371) is similar to that of Study 1 (r = .359), and I expect it will reach significance with an increased sample size.

The regression analyses presented in the current study revealed a significant relationship between vSTR-vmPFC connectivity and discounting rate, as was similarly observed in Hampton et al. (2016). Further, the results showed that this pathway is similarly predictive of mobile technology engagement as measured by the MTE. These findings together demonstrate evidence for a structural brain correlate for the behavioral patterns observed in Study 1. As this relationship arose within the frontostriatal reward pathway, this outcome is generally consistent with the phenomenon that was initially reported in Wilmer & Chein 2016, and was partially replicated in both Study 1 and 2: that the level of engagement with these devices is closely related to the subjective experience of reward. The presence of both of these relationships in this sample provides us with some insight into the relationship between MTE and discounting rate, with white matter connectivity between the ventral striatum and vmPFC serving as a biological substrate, and marker, of this relationship.

Consistent with previous research (van den Bos, Rodriguez, Schweitzer, & McClure, 2014), this study also revealed a significant relationship between discounting rate and vSTR-dlPFC connectivity. However, in contrast with what was observed in vSTR-vmPFC connectivity, the vSTR-dlPFC pathway was not a significant predictor of MTE scores in the present study. Therefore, the data presented by the current research do not provide any evidence that vSTR-dlPFC connectivity is a biological substrate of engagement with mobile technology devices.

One final important observation is the divergent directionality of the effects obtained in each hemisphere with regard to striatal connectivity. In analyzing both log(k) and MTE as a function of vSTR-vmPFC connectivity, the results indicated that right hemisphere streamlines were positively correlated with engagement and steeper discounting, while the left hemisphere was negatively correlated with the same behavioral outcomes. This discrepancy is not altogether uncommon in examining white matter tractography (Alm, Rolheiser, & Olson, 2016; Wouter van den Bos & McClure, 2013), and while it could indicate measure or statistical artifacts, it could be due to specific functions that are lateralized to one side or the other for these pathways. Since so much of what occurs during one's interactions with a smartphone is heavily based on communication, it is quite possible, for instance that language-based lateralization of smartphone behaviors is at play.

CHAPTER 8

GENERAL DISCUSSION

Taken together, the findings of the two studies presented in the current study demonstrate cognitive and neural links to heavy engagement with mobile technology devices. By including an objective measure of time spent on one's phone in the study design, I was able to determine that the self-report MTE questionnaire provides a reasonably accurate depiction of the degree to which individuals are invested in their smartphones. Both studies successfully replicated a key finding from Wilmer & Chein (2016): individuals who are more heavily invested in their mobile technology devices have a tendency to accept smaller, immediate rewards rather than wait for a larger reward. In contrast with the findings presented in Wilmer & Chein 2016, the results of the current research showed that the degree to which one engages with mobile technology could also be predicted by individual differences in reward sensitivity, rather than impulse control.

As discussed in the Introduction, previous literature has indicated that intertemporal preference as measured by the delay discounting task is a function of two related but separate cognitive traits: reward sensitivity and impulse control. Brain imaging evidence has demonstrated that these two traits can be isolated to distinct regions of the prefrontal cortex: the vmPFC is a locus of reward-related processing (Hampton, Bossaerts, & O'Doherty, 2006; O'Doherty, Kringelback, Rolls, & Andrews, 2001), whereas the dlPFC is associated with the exercise of control and inhibition of a response (Cieslik et al., 2013; Hoshi, 2006; Miller & Cohen, 2001).

Study 2 provides the first evidence of a relationship between vSTR-vmPFC connectivity and mobile technology engagement. As discussed above, this pathway has been implicated in a tendency toward reward-seeking behaviors, and these findings follow a consistent pattern with the behavioral results presented across both studies. In both Study 1 and Study 2, I found that reward sensitivity was correlated with MTE scores. Study 2 provided evidence for a structural correlate of this relationship in the frontostriatal reward pathway. This is distinct from the impulse control component of intertemporal preference, as I found no relationship between MTE scores and impulse control, and found that the vSTR-dlPFC pathway which has been implicated as a neural correlate for impulse control was similarly unrelated to MTE. Taken together, the results provide evidence that the relationship between mobile technology engagement and intertemporal preference is driven, at least in part, by reward sensitivity, and that this phenomenon is manifested in vSTR-vmPFC connectivity.

The most notable limitation of the findings presented in this research is the small sample size of Study 2. Consisting of only 16 individuals, this sample is quite susceptible to spurious relationships. As such, the analyses presented in this paper are presented as exploratory in nature, and will hopefully provide guidance for constructing future hypotheses for analyzing further data once more subjects are run in a continuation of this study. Additionally, although this replication and extension provides further confidence that there is a significant relationship between technology usage and discounting rate, it does not address the directionality of this effect. Specifically, it is still unknown whether heavy engagement with smartphones causes people to become more immediacy-oriented, or whether individuals who are innately more immediacy-oriented have a greater tendency to spend more time with their phones, or whether some third variable is driving those two behaviors independently. Having now demonstrated strong and replicable evidence of this relationship between mobile technology use and intertemporal preference, assessing the causation should be first priority for researchers moving forward.

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