2014

Compulsive Technology Use

Jeffrey A. Clements

FLORIDA STATE UNIVERSITY

COLLEGE OF BUSINESS

COMPULSIVE TECHNOLOGY USE

By

JEFFREY A. CLEMENTS

A Dissertation submitted to the
Department of Management
in partial fulfillment of the
requirements for the degree of
Doctor of Philosophy

Degree Awarded:
Spring Semester, 2014

Jeffrey Clements defended this dissertation on April 4, 2014.

The members of the supervisory committee were:

Ashley Bush
Professor Directing Dissertation

Charles Hofacker
University Representative

David Paradice
Committee Member

Deborah Armstrong
Committee Member

The Graduate School has verified and approved the above-named committee members, and certifies that the dissertation has been approved in accordance with university requirements.

Dedicated to my wife, the love of my life

ACKNOWLEDGEMENTS

So many people supported me during this process. Too many to name by name. I am grateful for your feedback, your encouragement and your thoughts and prayers.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

Information technology engages users in a variety of ways. No longer confined to information systems in organizational contexts, technology has become much more pervasive and personalized. As individuals are increasingly exposed to the types of triggers that prompt automatic technology engagement, technology use has moved beyond the bounds of intentionality. This leads to the development of technology-use behaviors that may become automatic or difficult to control. Individuals can begin to develop spontaneous-use behaviors and feel compelled to interact with the systems they use. This new type of system use is called compulsive technology use.

Compulsive technology use is defined as spontaneous interaction with technology that is unintentional, uncontrollable, effortless, and efficient. Compulsive technology use is effortless and efficient in that it does not interfere with other cognitive processes. Compulsive technology use is unintentional in the sense that no act of will is required to initiate it. Compulsive technology use is uncontrollable in that a person has difficulty controlling the process once it has been initiated. But little is known about what drives compulsive technology use. This dissertation explores the phenomenon of compulsive technology use in the context of mobile applications. The roles of technology habit and perception of sunk costs in the development of compulsive technology use will be addressed. In addition, identifying the technological drivers of technology habit will contribute to the understanding of how the characteristics and features of technology influence compulsive technology use.

CHAPTER ONE

INTRODUCTION

1.1 Technology Engagement

One of the primary ways to ascertain whether a technology is successful is to determine how much the technology is being used (Mason and Mitroff, 1973). MIS research has a long tradition of using individual engagement as a proxy for system success (DeLone and McLean, 1992). Research has demonstrated that technology has the capability to engage users in a variety of ways (Kim and Malhotra, 2005). The bulk of this research has focused on the intentional use of information systems. These systems have primarily been mandatory systems implemented by organizations.

In this traditional technology context, technology engagement is triggered by the organizational mandate to use the new system. In this view, research has focused on an individual's behavioral intention to engage with a system. However, not all technology use is a product of an organization implementing a new mandatory use system with which its employees intentionally interact. Arguably, the technologies most used today are used outside of the strict boundaries of intentional interaction with mandatory technologies in organizational settings.

In this new technology context, technology engagement is not triggered by organizational mandate. Identifying what triggers technology engagement of voluntary technologies in personal settings has yet to be fully understood. In this context, behaviors are often performed non-rationally and automatically. This is a demonstration that technology engagement can often be a product of technology features triggering certain usage behaviors outside of one's awareness. Research in this new technology context is in its naissance because we have yet to fully understand this new type of technology engagement.

Because research has yet to fully explore technology usage behaviors of voluntary technologies, we have been unable to comprehend the constituents of technologies in this new technology context and what effect technology may have on behavior. The bulk of research related to usage behaviors has stemmed from the core MIS dimension of information system use. In this dimension of information system use, research has examined the acceptance (Davis et al., 1989), adoption (Moore and Benbasat, 1991), and continued use (Bhattacherjee, 2001) of technologies. Research in usage behavior has primarily focused on an individual's behavioral intention to use a mandatory information system in the context of their occupation (Bhattacherjee et al., 2008; Davis et al., 1989; Venkatesh and Davis, 1996; Venkatesh et al., 2003). Whether the stage of system use was the initial decision to use a system or a continued decision to keep using a system, research in this stream has been based on theories of intentional behavior. Two dominant theories have been the theory of reasoned action (Ajzen and Fishbein, 1975), and the theory of planned behavior (Ajzen, 1991). Both theories are grounded in the core belief that behavior is predominately planned and intentionally performed. Therefore, MIS research based on these theories has focused on usage behaviors that are planned and intentional.

However, recent research has demonstrated that behavior can be neither planned nor intentional (Kim, 2009; Kim and Malhotra, 2005; Kim et al., 2005). This research has suggested that MIS researchers need to develop new theories for behaviors that are unplanned and unintentional (de Guinea and Markus, 2009). Research in this stream has looked at how the predictive power of behavioral intention can be inhibited by stronger psychological mechanisms which come into play (Limayem et al., 2007). Several mechanisms such as impulsiveness (Wells et al., 2011), sunk costs (Polites and Karahanna, 2012), habits (Venkatesh et al., 2012a), automatic behaviors (Kim et al., 2005) and addictions (Turel et al., 2011a) have been shown to drive IS use behaviors non-rationally. However, this research is still in its infancy as researchers have yet to identify how these unplanned, automatic and uncontrollable behaviors come to be. The primary goal of this dissertation is to begin to address this gap in our understanding of what is triggering this non-intentional and compulsory technology engagement behavior—a behavior which up to now has predominantly been identified by popular press.

1.2 Motivation

Approximately 9 million Americans could be labeled as pathological computer users addicted to the technology to the detriment of work, study, and social life (Byun et al., 2009; Young, 1998). There are numerous popular news articles about how individuals are becoming addicted to some form of technology. "When we think of addiction, most of us think of alcoholism or drug abuse. But the easy access, anonymity, and constant availability of the Internet, email, texting, chatting and twittering has led to a new form of compulsive and dependent behavior - techno-addicts. The same neural pathways in the brain that reinforce dependence on substances can reinforce compulsive technology behaviors that are just as addictive and potentially destructive" (Small, 2009). Compulsive technology use is defined herein as spontaneous interaction with technology that is unintentional, uncontrollable, effortless, and efficient. Compulsive technology use is a form of technology behavioral addiction in which an individual engages in a specific behavior—specifically with technology—for relief, comfort, or stimulation, and which results in discomfort or unease of some type when discontinued (Porter and Kakabadse, 2006).

Frequently these popular tech articles offer advice on how to be less addicted and less compelled to use your favorite gadget or program. These popular press “technology experts” frequently offer advice on how to regain a healthy balance and sense of control over the technologies we have been enslaved to. Examples include articles about how the light on tablet computers mimics daylight and thus one should not use it before bed as it can lead to sleep deprivation (Adams, 2012), or articles on how to train oneself to resist the impulse to check-in on Facebook (Perkins, 2012), or articles on how to manage the technology device features as to not provide notifications when something said or done is “tagged”, “re-pinned”, or “commented on” (Soong, 2008). A recent extreme example of compulsive technology use to grab popular press headlines is that of “Sleep Texting” (Bindley, 2013) in which individuals receive and respond to text messages while asleep and have no recollection of doing so when awake. Recent research has demonstrated that this type of compulsive technology interaction may be partially attributable to individuals texting and reading texts without awareness, control, attention, and intention (Bayer and Campbell, 2012). What these articles have yet to fully address, and what research has yet to fully address, is what is driving such high levels of compulsory technology interaction.

A recent example of research looking at how technology use can become a “bad habit” can be seen in Turel and Serenko’s (2012) examination of the benefits and dangers of enjoyment with social networking sites. Generally information systems enjoyment is a desirable and positive outcome of IS use. Their research showed that enjoyment can be a key driver in the formation of adverse technology-related addictions through the positive reinforcement it generates (Turel and Serenko, 2012). This is a demonstration that enjoyment both contributes to high engagement—a positive outcome—and a strong pathological and maladaptive psychological dependency on technology—a negative outcome. For the extremely addicted technology user, several negative outcomes of this type of compulsive technology use such as social anxiety, loneliness and depression have been identified (Tokunaga and Rains, 2010).

However, compulsive technology use is not necessarily a bad thing as addictive technology behaviors can mean big money for businesses. The compulsive technology user represents the ultimate consumer who is unwilling or unable to say no to the next upgrade, the newest feature roll-out, or the next game release. Despite the popularity of the subject matter, very little research has engaged compulsive technology use head on. Research has yet to identify what is causing individuals to become so compelled to interact with technology.

To explore these questions, the focus of this dissertation will be on the core concept of compulsive technology use—defined as spontaneous interaction with technology that is unintentional, uncontrollable, effortless, and efficient. Technology use can be viewed on a continuum from very intentionally driven use on one end, to automatic driven pathological addiction on the other end. Compulsive technology use is a type of technology use which falls just short of a pathological behavioral addiction to technology. Behavioral addiction is defined as engaging in a specific behavior for relief, comfort, or stimulation, and which results in discomfort or unease of some type when discontinued (Porter and Kakabadse, 2006). Compulsive technology use is spontaneous, unintentional and difficult to control, however it lacks the negative maladaptive qualities of addiction. Compulsive technology use follows a type of automatic sequence described by Ajzen and Fishbein (2000) in that it is behavior that 1) occurs without awareness, 2) is difficult to control, 3) is effortless and efficient, and 4) is unintentional in the sense that no act of will is required to initiate it (Ajzen and Fishbein, 2000).

While the discussion of technology addiction is not new, very little research on compulsive technology use has been done. Much research which relates to compulsive technology use has been on video game addiction. Early research on the behavioral addiction of playing electronic games(Orford, 1986) warned that this phenomenon appears to be an "instance of new technology producing an activity that has the necessary features to give it potential for excess, and catching society unawares before it can anticipate the dangers and instigate the sorts of controls that have grown up around more traditional pursuits, such as drinking alcohol or gambling" (Porter and Kakabadse, 2006). Other research has examined similar phenomena such as problematic internet use (Davis et al., 2002), internet addiction (Yellowlees and Marks, 2007), and obsessive compulsive use (Shapira et al., 2000).

1.3 Development

The overarching research question guiding this dissertation is "*What drives compulsive technology use?*" To explore this question this dissertation will focus on the following research question:

(1) "*How do the characteristics of a technology influence compulsive technology use?*"

Understanding the phenomenon of compulsive technology use has implications for research and practice. From a developmental standpoint, information systems platforms can be purposefully designed to incorporate technology features which either enable or inhibit compulsive interaction with the system. This will allow fewer but more efficient systems to be designed with the necessary features to promote the type of technology engagement desired. If extremely high compulsive engagement is desired, then certain functionalities which are pre-programmed into a platform can be "switched-on" by those developing on the platform. If the desired functionality is more utilitarian and developers wish to inhibit compulsive interactions, then those certain functionalities which engage compulsive behaviors can be "switched-off" by those developing on the platform.

From a research standpoint, this fills a gap in a call for research with a design science orientation (Hevner et al., 2004). Understanding the technology features which enable high levels of spontaneous interaction will allow for the study of more efficient voluntary use systems. This knowledge can aid researchers in making more informed design decisions. This implies that the design of voluntary use systems can impact an individual's future use of the system.

Understanding compulsive technology use will also further our understanding of technology behaviors that are not motivated by classical theories of behavioral intent. This answers the call for MIS research to use behavioral frameworks which are far more emotional, less rational and unintentional (de Guinea and Markus, 2009) to understand why individuals interact with technology. Much of human behavior can be classified as automatic (Aarts et al., 1998) and understanding compulsive technology use will allow us to understand how technology can drive automatic and non-rationally driven technology usage behaviors.

The context of this dissertation is mobile applications. "Apple's founder, Steve Jobs spoke about changing the world, and he did so through apps" (Graydian, 2013). In the summer of 2008, the Apple iPhone hit the world market. With that debut came the Apple App store where mobile applications (apps) for just about anything could be created and distributed. As of January 2013, there are over 775,000 mobile apps available for the iPhone and over 250,000 available for the iPad (Costello, 2013). Google Play, formerly known as the Android Market, is the digital app marketplace for Android users which was launched in October of 2008. As of January 2013, there are over 700,000 apps for Android devices (Google, 2013). This incredible growth of mobile apps has not only altered the smartphone landscape, but it has ushered in the modern era of ubiquitous, intelligent, and connected devices. Current estimates show that by 2015 there will be over 182 billion mobile app downloads across all platforms and that mobile app revenue will rise to $36.7 billion (Kim, 2011). Industry analysis shows that the top 25 US developers collectively made $60 million in app revenue (which accounted for 50% of the total US app revenue) during the first 20 days of November 2012 (Canalys, 2012). The overall impact and success of mobile applications cannot be argued. However, understanding what makes an individual develop compulsive interaction behaviors with mobile applications has yet to be explored.

To address the question of what drives compulsive technology use, I begin by reviewing the relevant literature on technology use. I start with a look at intentional system use—the first stage of system use in which individuals choose to use a given technology—as captured by studies looking at information systems (IS) acceptance. Then I review the next progression of system use research, the ongoing and intentional choice to continue using a technology—IS continuance. Following that, I will review the literature that has more relevance to system use that is not strictly intentional. Next, I will discuss the development of habitual use or IS habit and review the extant habit literature. I will conclude the overall literature review by a review of the literature on technology addiction as I develop the concept of compulsive technology use. Compulsive technology use represents a stage of system use which is driven by something other than behavioral intent. Compulsive technology use encompasses a stage of use which has moved beyond the initial acceptance of a technology and moved beyond the intentional decision to continue using a technology (i.e., continuance). It is a type of technology use which has extended beyond the goal orientation and intentionality of technology habit.

Following the literature review, I will discuss the theoretical framework which informs my conceptualization of compulsive technology use. First, I will discuss Simon's (1947) theorizing on automatic behaviors, which provides a lens to understand compulsive technology use. Next, I will briefly review classical conditioning and operant conditioning. Finally, I will employ the framework of automatic behaviors (Simon, 1947) to develop a conceptual model of compulsive technology use.

Following the theoretical development discussion I will further develop the research model to explore compulsive technology use. I will do this in two parts. First I will discuss the technology mechanisms of behavioral persistence which contribute to compulsive technology use. The technology mechanisms of persistence—technology habit and perception of sunk costs—will be explored. Second, I will discuss the technology mechanisms of behavioral initiation which serve to engage usage behaviors. These technology mechanisms of behavioral initiation are antecedents to the identified technology mechanisms of behavioral persistence. In doing so I discuss the antecedents to technology habit— technology instability, technology complexity, and technology-enabled triggers.

Following the development of the research model of compulsive technology use, I will discuss the research methodology used to explore the research question. I will discuss the chosen research design and issues related to the measurement for the research model's variables of interest. Then, I will discuss the analysis methodologies chosen to test the research model and the hypotheses. I conclude with a discussion of the research contributions and practical implications of the dissertation.

CHAPTER TWO

LITERATURE REVIEW

2.1 Information Systems Use

Ascertaining the success of an information system has been at the core of MIS research since its inception (Mason and Mitroff, 1973). MIS researchers have extensively debated what the ultimate measure for system success should be (Brancheau and Wetherbe, 1987; Niederman et al., 1991; Orlikowski and Baroudi, 1991; Orlikowski and Robey, 1991). The seminal work of Delone and McClean (1992) proposed that progress toward an MIS cumulative tradition dictated a significant reduction in the dependent variable measures for system success. To address this problem, Information System Use was proposed as a core dimension to gauge system success (DeLone and McLean, 1992).

Understanding why people choose to adopt, choose to use, and choose to continue to use a specific information system (IS) has been a topic extensively researched in the MIS field (Bhattacherjee, 2001; Davis et al., 1989; Tiwana and Bush, 2005; Venkatesh et al., 2003). Extant literature provides numerous models and frameworks which inform our understanding of phenomena related to various stages of intentional IS use behaviors (Al-Natour and Benbasat, 2009; Thompson et al., 1991; Venkatesh and Davis, 1996). In general, research has progressed in stages looking first at IS acceptance as a measure of system success. Next, research began to investigate IS continuance (or continued use) as a measure of system success. More recently research has begun to explore habitual IS use as a measure of system success.

2.2 Information Systems Acceptance

One of the first frameworks in this research stream, the technology acceptance model (TAM), focuses on predicting an individual's attitude towards accepting a new technology in the workplace (Davis et al., 1989). Based on the theory of reasoned action (TRA) (Fishbein and Ajzen, 1981), this research suggested that two main constructs—ease of use and usefulness—could explain a large amount of variance in an individual's attitude towards acceptance. Ease of use is defined as a belief that the information system is relatively easy to use. Usefulness is defined as a belief that the information system is useful in completing an assigned task. This model showed that perceived ease of use and perceived usefulness positively affected an individual's intention to use and accept an information system. Results of this research showed that perceived ease of use and perceived usefulness were able to explain near 60% of the variance in an individual's attitude towards acceptance. When compared to other models of system use which were far more complex and explained far less variance (Ives et al., 1983), TAM spurred research in many directions and several variations or extensions of TAM have been proposed (Moore and Benbasat, 1991; Taylor and Todd, 1995).

Moore and Benbasat's (1991) work produced the innovation diffusion model. By adapting Davis et al.'s (1989) perceived usefulness and the perceived ease of use, the innovation diffusion model measured relative advantage and complexity. Similar work by Taylor and Todd (1995) addressed the fact that prior TAM research failed to take into account whether previous experience affected the perceived usefulness and perceived ease of use of an information system. Their extended version of TAM incorporated social influences, behavioral control, and previous experience.

Other research has extended TAM by introducing new variables to further explain technology acceptance. Agarwal and Prasad (1998) introduced the construct of personal innovativeness to TAM. Dishaw and Strong (1999) looked at how task-technology fit (i.e., for a given task, how well suited is a particular technology) could be integrated with the technology acceptance model. Agarwal and Karahanna (2000) used the core concepts of the technology acceptance model to look at system acceptance but added cognitive absorption, playfulness and self-efficacy. Venkatesh and Davis (2000) added subjective norm into the technology acceptance model as an important determinant of system acceptance. Other research has looked at how peer influence affected the core concepts of TAM in a healthcare setting (Chau and Hu, 2002). Similar research has looked at gender (Gefen and Straub, 1997), trust (Gefen et al., 2003; Kim et al., 2009a; Paul and McDaniel, 2004), habits (Gefen, 2004), and technology readiness (Walczuch et al., 2007) as constructs which influence technology acceptance.

The overarching contribution of TAM research has generally been limited to the acceptance of information systems in the work place. However, some research has examined technology acceptance in different contexts. Research has applied the technology acceptance model to help explain users' acceptance of the World-Wide-Web (Moon and Kim, 2001). Similar work has used the technology acceptance model to explore the acceptance of online financial instruments (Al-Somali et al., 2009) and online auctions (Wells et al., 2011). Research has also applied the technology acceptance model to explore the acceptance of specific technologies such as interface agents for email notification (Serenko, 2008), RFID technology (Müller-Seitz et al., 2009), and virtual banking technology (Lee, 2009).

Venkatesh, Morris, Davis and Davis (2003) proposed the Unified Theory of Acceptance and Use of Technology (UTAUT) to synthesize these various adoption and acceptance models. This research assessed the similarities and differences of several competing technology acceptance models, (1) the Technology Acceptance Model, (2) the Theory of Planned Behavior, (3) the Model of PC Utilization, (4) the Innovation Diffusion Theory, and (5) the Social Cognitive Theory. Each model was tested against UTAUT to determine which model was best able to comprehensively predict information systems use. UTAUT significantly outperformed each of the competing models in predicting the variance in behavioral intention (70%) and the variance in actual technology use (50%) (Venkatesh et al., 2003). The key theoretical contribution from this work is that UTAUT identified the key constructs that predict behavioral intention to use a technology in organizational contexts.

Research has since extended the UTAUT model in a variety of ways (Venkatesh et al., 2012b). First, UTAUT has been extended to include new contexts such as new technologies (Chang et al., 2007), new user populations (Yi et al., 2006) and new cultural settings (Gupta et al., 2008). Second, it has been extended to include new theoretical constructs to expand the scope of UTAUT's endogenous variables (Chan et al.; Sun et al., 2009). Third, it has been extended to include exogenous predictors of the core UTAUT variables (Neufeld et al., 2007).

More recently, a more comprehensive version of the unified theory of acceptance and use of technology (UTAUT2) was introduced (Venkatesh et al., 2012b). UTAUT2 takes the core concepts from the first unified theory of acceptance and use of technology and incorporates hedonic motivation, price value, and habit into the model. As a result UTAUT2 increased the variance explained in behavioral intention (from 70% to74%) and technology use (from 50% to

52%). The key theoretical contribution of UTAUT2 is the identification of additional constructs and relationships which are applicable in a consumer use context rather than the traditional organizational context of TAM/UTAUT(Venkatesh et al., 2012a).

In summary, research on the acceptance of technology has progressed from TAM to UTAUT to UTAUT2. The common thread of this research is that it has been focused on an individual's intention to use an information system in an organizational context. The stage of system use has been the initial acceptance of technologies. The type of technology studied has varied though it generally has been a mandatory use technology in work settings(Chan et al., 2010). Overall this research has provided a foundation to understand the variables which contribute to the initial acceptance and use of technology. The next section will explore the next stage of system use—post acceptance/ continued use or IS continuance.

2.3 Information Systems Continuance

Though the initial use of an information system is an important indicator of system success, it does not necessarily lead to desired managerial outcomes unless the use continues (Kim and Malhotra, 2005). Research that moves beyond the initial adoption or acceptance of technology has generally looked at IS continuance (Bhattacherjee, 2001; Bhattacherjee et al., 2008). The goal of post-adoption research is to understand both "how" and "why" individuals use certain technologies to their fullest potential in the work place (Chin et al., 2003). The focus of IS continuance research—though grounded in the concepts and constructs of TAM and UTAUT— has moved beyond the adoption stage of system use to look at the post-adoptive behaviors associated with information technology enabled work system (Jasperson et al., 2005). IS continuance is defined as a repeated decision to continue using an information system after the system has been initially accepted (Kim et al., 2007). IS continuance research examines the decision to continue using technology over the long run. IS continuance research is in contrast to IT acceptance which focuses on the initial or first-time decision to use a technology (Bhattacherjee et al., 2008). Though research on the initial acceptance of a technology was an important first step toward understanding IS success, the long-term sustainability of a technology and its eventual success depends on its continued (rather than first-time) use (Bhattacherjee, 2001).

IS continuance research—grounded in the concepts of expectation confirmation theory (Brown et al., 2012)—has shown that individuals develop expectations about how easy to use and useful a system is. If these expectations are subsequently confirmed as the individual interacts with the system, then the individual will feel satisfied. Satisfaction in turn has been shown to contribute towards IS continuance intentions. Thus, IS continuance is conceptualized as a series of intentional decisions to use a system—driven by heightened perception of usefulness and satisfaction (Bhattacherjee, 2001; Venkatesh et al., 2008).

IS continuance research has expanded on the original model of continuance and extended continuance into a variety of new contexts (Al-Natour and Benbasat, 2009; Chen, 2007; Venkatesh and Goyal, 2010). For example, Chen (2007) proposed a continuance model in which an individual's intent to continue using a given technology is influenced by both contextual factors (e.g., social capital) and technological factors (e.g., satisfaction, system quality, knowledge quality). Pre-usage expectations were found to influence the contextual and technological factors and both factors were found to exert significant impact on continuance intentions (Chen, 2007).

IS continuance research has also studied the post acceptance phenomenon of discontinuance (i.e., the choice to discontinue using an IS after initial acceptance). Venkatesh and Goyal (2010) directly questioned the expectation-confirmation relationship of IS continuance and suggested an expectation-disconfirmation relationship instead. Expectation-disconfirmation research uses the concepts of cognitive dissonance, realistic job preview, and prospect theory as a foundation for expectation-disconfirmation (or discontinuance) in information systems. This work demonstrates that disconfirmation is an undesirable phenomenon, as evidenced by low behavioral intention to continue using a system for both positive and negative disconfirmation (Venkatesh and Goyal, 2010).

IS continuance research has also highlighted the importance of the IT artifact. Al-Natour and Benbasat (2009) proposed that the relationship between an IT artifact and a user affects the beliefs the user forms about the outcomes of using the artifact. They propose that past interactions with a technology influence future continued use (Al-Natour and Benbasat, 2009). Thus our past adoption decisions continue to influence our current continuance decisions with a certain path dependency (Kim and Malhotra, 2005). Similar research developed an expertise-sharing network continuance model which demonstrated how certain factors that emerge through irretrievable investments by individual users after initial adoption influenced their continued use of the system (Tiwana and Bush, 2005). The intentional continuance of mandatory use technologies is the common theme in this line of research(Hsieh et al., 2012).

IS Continuance research has also been applied to Internet use (Hsu and Chiu, 2004). The Web Acceptance Model (WAM) showed that an individual's experience on a website is the moderating factor in determining continued use of the website (Castaneda et al., 2007) Similar IS continuance research has looked at web-based applications (Limayem and Cheung, 2008). Research in this area has used the commitment-trust theory—an expectation-confirmation model—in combination with several TAM related variables to develop a model of IS continuance of web-based applications(Vatanasombut et al., 2008). This work has demonstrated that relationship-commitment and trust can be used to predict continuance intention (Morgan and Hunt, 1994; Vatanasombut et al., 2008).

IS continuance research has also examined continuance intentions in contexts that may not be considered mandatory—such as mobile computing applications (Zhou, 2013), mobile video viewing (See-To et al., 2012), micro-blogging (Agrifoglio et al., 2012; Zhao and Lu, 2012), and social virtual world services (Schwarz et al., 2012; Sun et al., 2012; Zhou et al., 2012). Research in this stream has identified several external drivers of continuance intentions such as: affective commitment (being attracted to) and calculative commitment (being locked in) (Zhou et al., 2012); identity (Schwarz et al., 2012); intrinsic motivation (Agrifoglio et al., 2012); task complexity and self-efficacy (Sun et al., 2012); perceived interactivity, control, playfulness, connectedness and responsiveness (Zhao and Lu, 2012).

Continuance research has been applied in a marketing context to explore relationship commitment (Gruen et al., 2000) and repeat customer purchases (Devaraj et al., 2002). Similar studies have applied the IS continuance model to understand a variety of consumer continuance behaviors. Research in this stream has placed emphasis on the impact of the psychological factors which lead to consumer repurchase continuance such as trust ((Ba and Pavlou, 2002; Kim et al., 2009a; Kim et al., 2009b) and satisfaction formation (Khalifa et al., 2002; Khalifa and Liu, 2007). Other studies have placed emphasis on the impact of product/service characteristics, medium characteristics and merchant and intermediary characteristics on consumer repurchase continuance (Cheung et al., 2005). Research in this vein has also explored technology's role in electronic/ mobile commerce continuance (Hausman and Siekpe, 2009). Similar research has looked at the impact of web page design factors such as navigation, security, search attribute and shopping aids (Liang and Lai, 2002) to predict future continuance.

Research has also directly expanded on Bhattacherjee's original IS continuance model by suggesting moderating effects to IS continuance intention and IS continued usage (Limayem and Cheung, 2008). This research studied an internet-based learning technology in a longitudinal setting and found support for the hypothesis that the strength of intention to predict continuance would be weakened by a high level of IS habit. Similar research has identified the importance of repeated behavioral patterns and suggested past use would likely be a good proxy for habit as well as a reliable predictor of future use (Kim and Malhotra, 2005). Other moderators for continuance intention have been identified such as experience (Gupta and Kim, 2007) and socio-economic advantage and disadvantage (Hsieh et al., 2008).

Recent work by Bhattacherjee, Perols and Sanford (2008) proposed a theoretical extension of the IS continuance model. This work linked continuance intention to behavior and elaborated on the contingent factors that shape IS continuance intention and behavior. By drawing from cognitive psychology literature the authors conceptualized perceived behavioral control in the dimensions of IT self-efficacy and facilitating conditions. They found self-efficacy to be related to continuance intention and facilitating conditions to be related to behavior. The key theoretical contribution of this work is that it extended the theoretical boundaries of the IS continuance model and clarified the concept of perceived behavioral control in an IS setting (Bhattacherjee et al., 2008).

Work that has built on this updated model of IS continuance has studied the impact of user satisfaction with mandated customer relationship management (CRM) system use (Hsieh et al., 2012). The focus of this work showed that the satisfaction leading to IS continuance has a positive impact on several outcome variables such as employee service quality and job dedication. Similar work has looked at mandatory continued use of healthcare management systems (Moores, 2012). The theoretical contribution of this work is that several new outcomes which stem from user satisfaction of mandatory IS continuance were identified.

In summary, IS continuance research has extended our understanding of the intentional choice to use an information system into a secondary stage of use. This secondary stage is the repeated choice to continue using an information system after the initial stage of acceptance—also referred to as IS continuance. IS continuance research has only recently begun to examine the continued use of technologies in voluntary contexts and non-work related environments. The key thread tying this research together is that the focus is on an individual's conscious intention to continue with a system. Several moderators of continuance intention have recently been identified. The predominant moderator of continuance intention—habit—will be discussed next.

2.4 Information Systems Habit

The next stream of system use research moves beyond the intentional continued use of technology. As one of the most mature streams of MIS research, understanding individual acceptance and use of technology has primarily looked at the behavioral intention to use a technology in organizational contexts (Venkatesh et al., 2012a). Research has noted that there are predictors of behavior in general and of system use in particular that have been largely absent from current models of system use. This research suggested that as behaviors become routinized, habit will likely play a more influential role than behavioral intention or behavioral expectation (Venkatesh et al., 2008). System use research has recently begun to look beyond behavioral intention as the key predictor of technology use and has begun to investigate the role of habit as a critical predictor of technology use (de Guinea and Markus, 2009; Limayem et al., 2007; Polites and Karahanna, 2012; Venkatesh et al., 2012a).

Early MIS research on system use identified the theoretical importance of habit but excluded any habit construct from analysis (Thompson et al., 1991). Habit has generally been classified and operationalized in two distinct ways. The first operationalization views habit as a prior behavior (Kim and Malhotra, 2005). The second operationalization views habit as the extent to which an individual believes the behavior to be automatic (Limayem et al., 2007). The role of habit in motivating behavior has long been acknowledged (Triandis, 1971). Triandis (1971) defined habit as "situation-behavior sequences that occur without self-instruction." Habit has also been defined as "learned sequences of acts that have become automatic responses to specific cues, and are functional in obtaining certain goals or end-states" (Verplanken and Aarts, 1999).

Habit has also been viewed as a routine in the occupational science literature. In this sense habit is defined as "sequences chaining together daily activities, enabling complex action in the world, and efficiency of time and attention" (Clark et al., 2007). These types of habits are usually automatic until they are disturbed or unsuccessful. Routine-type habits are resistant to change but they can be disrupted by internal or contextual life changes. Following this line of thought I use the definition proposed by Polites and Karahanna (2012) and define habit as "goal-oriented behavior which we establish from previous experiences."

Research on habit has revived a theoretical foundation—which was once present in early IS research (e.g., Thompson et al., 1991), but has since been forgotten or replaced by the prominence of work based on the theory of reasoned action (TRA) and the theory of planned behavior (TPB). Beyond an individual's attitudes which lead to behaviors—as noted by Ajzen and Fishbein's (1981) theory of reasoned action which is the foundational theory for TAM (Davis, 1989)—there are previous behaviors that can lead to future behaviors. This is the foundation for habit driving behavior which stems from Triandis' (1971) theory of attitudes and behaviors, in which habit is an important determinant of behavior. Triandis' theorizing has been well received by other disciplines (e.g., Marketing, Organizational Psychology) and research on IS habit brings this theorizing back into consideration.

A contribution of Limayem et al.'s (2007) research is the focus of habit's effect on behavioral intention. This work hypothesized that an individual's IS habits should decrease behavioral intentions. The authors used Bhattacherjee's (2001) IS continuance model to test this hypothesized effect of habit on an individual's intention to continue using an information system. By integrating past research on habit with IS continuance they further suggested that the antecedents of behavioral intent were related to the drivers of habitualization (Limayem et al., 2007). Satisfaction and frequency of use were found to be related to habit. They also found that habit significantly limited the predictive power of intention. Thus work on behavioral intention which does not account for habit may be overstating the assumed relationship between intention and actual behavior (Chiu et al., 2012). This contribution suggests that habit may play a bigger role in IS use models which are predicated on intention to use technology (i.e., TAM, TAM2, UTAUT). Research reflecting this relationship has used habit as a moderator between trust and intention (Chiu et al., 2012; Lankton et al., 2012)

Similar work has demonstrated the importance of habit in information systems research. The integrative framework of technology use (IFTU) recently proposed by Kim (2009) posited that in order to fully explain post-adoption phenomena, four mechanisms should be taken into account simultaneously in a unified model. The fist mechanism is reason-oriented action. This mechanism is concerned with the evaluation-behavior relationship (i.e., TAM). The second mechanism is sequential updating. This mechanism is concerned with the sequential updating of judgments as prior evaluations can determine current evaluations (i.e., the evaluation-evaluation relationship). The third mechanism is feedback. The feedback mechanism is concerned with the behavior-evaluation relationship as prior behavior influences current evaluations. The fourth mechanism is habit. The habit mechanism is concerned with the behavior-behavior relationship as prior behavior can affect current behavior. Thus, in order to fully understand post-adoptive technology behaviors, habit must be taken into account (Kim, 2009).

MIS research building on these concepts has studied the phenomenon of IT switching—a consequence in which a user switches from one technology to another. This research demonstrated that IT habits could not be created because of the dissatisfaction individuals associated with a given technology (Bhattacherjee et al., 2012). Similar work has explored repeated media consumption behavior as a matter of habit rather than a repeated continuance type decision. This work conceptualized media habits along a continuum from consciously enacted behaviors to those that are activated and driven automatically by external stimuli (LaRose, 2010). Important drivers related to habit development have been identified such as IT identity (also referred to as self-image congruity), and regret (Kang et al., 2009). Other drivers of habit that have been identified are familiarity, value and satisfaction (Chiu et al., 2012).

Research in behavioral psychology on habit has generally viewed habit through the lens of classical conditioning and the stimulus-response theory. Habit in this sense is thought of as a conditioned reflex and is defined as "behaviors learned through conditions, motivated by physiological reward, triggered by environmental stimuli" (Clark et al., 2007). Stimulus-response theory (Hall and Lindzey, 1957) suggests that humans can be conditioned to associate a conditioned stimulus (such as the presence of technology) with an unconditioned stimulus (such as interaction with technology). It is viewed as an automatic and unconscious behavior which persists until patterns of reinforcement are altered. As such, the mere presence of technology could lead to automatic use of the technology. This coincides with IS research that has used facilitating conditions as an antecedent to IS use (Thompson et al., 1991). In support of this phenomenon, researchers have found facilitating conditions to have a direct effect on actual use when developing the UTAUT model (Venkatesh et al., 2003), meaning that having strong facilitating conditions (i.e., the presence of technology) directly contributes to technology use.

The impact of habit on technology use has been studied in a variety of contexts. Research has looked at microblogs such as Twitter (Barnes and BöHringer, 2011), social networking sites such as Facebook (Lankton et al., 2012), software piracy (Yoon, 2011), and online shopping venues such as Yahoo (Chiu et al., 2012). The impact of habit on the adoption of new technologies has also been identified. Recent work by Polites and Karahanna (2012) showed that the habitual use of a current technology along with perceived transition costs and perceived sunk costs encourage the formation of technology inertia—a phenomenon in which organizations tend to persist with a given technology once it has been implemented. The negative outcome of incumbent system habit (i.e., habits with currently used technology) on the acceptance of a new technology stands as a novel contribution of this research (Polites and Karahanna, 2012). Similar research has looked at how the choices consumers make could be influenced by skill-based habits of use. Skill-based habits of use are defined as goal-activated automated behaviors that develop through the repeated consumption or use of a particular product. This research found that skill-based habits of use could explain how consumers become locked into a currently used product (Murray and HÄUbl, 2007).

In summary, more recent research has begun to include habit into models of technology use. The role of habit as a moderator has been examined and several drivers of habit have been identified. Recent IS theorizing by de Guinea and Markus (2009) has suggested we rethink our current conceptualizations of habit. They suggest that habit can become far more automatic and unintentional than our present conceptualizations. Instead of using theories of planned behavior and reasoned action with habit as a moderator, their theorizing suggests we look to theories of unplanned behavioral and unreasoned action (de Guinea and Markus, 2009). Building on this work, I will next develop a new conceptualization of technology use—compulsive technology use.

2.5 Compulsive Technology Use

Compulsive technology use refers to spontaneous interaction with technology that is unintentional, uncontrollable, effortless, and efficient. Compulsive technology use taps into those aspects of doing something that is unplanned and unreasoned as suggested by de Guinea and Markus (2009). IS habit differs from compulsive technology use on several fronts. The first deals with goal orientation and the second deals with intention.

First, IS habit is conceptualized as a goal oriented behavior which we establish from previous experiences. In this sense habits are still intentionally driven and purposeful in achieving our goal. For example, an individual has the goal of connecting with friends and so develops the habit of sending a tweet out on twitter each day after work to say hello. In contrast, compulsive technology use is conceptualized as a context driven behavior. For example, the same individual who has developed a habit of sending a tweet out after work to his friends now finds himself spontaneously checking in with twitter during a work meeting. Though the behaviors appear very similar on the outside, goal orientation is not driving the compulsive behavior.

Second, habits are intentional, planned and reasoned. The individual intends to say hello to his friends on twitter and so plans to send a tweet after work. In contrast, compulsive technology use is unintentional, unplanned and unreasoned action. The individual has not planned to check-in with twitter during a work meeting, but finds himself spontaneously doing so. As such, compulsive technology use is conceptualized as a non-intentional behavior that is engaged automatically and spontaneously. A similar example of this type of behavior that differs from intentionally driven habits is found in research on compulsive texting. Research on texting while driving has demonstrated that this type of compulsive technology interaction may be partially attributable to individuals texting and reading texts without awareness, control, attention, and intention (Bayer and Campbell, 2012).

An example of research looking at how technology use can move along the continuum past "normal habits" and can become a more compulsive "bad habit" can be seen in Turel and Serenko's (2012) examination of the benefits and dangers of enjoyment with social networking sites. Generally information systems enjoyment is a desirable and positive outcome of IS use. Their research showed that enjoyment can be a key driver in the formation of adverse technology-related addictions through the positive reinforcement it generates (Turel and Serenko, 2012). Thus enjoyment both contributes to high engagement—a positive outcome—and a strong pathological and maladaptive psychological dependency on technology—a negative outcome. Several negative outcomes of this type of technology use such as social anxiety, loneliness and depression have been identified (Tokunaga and Rains, 2010).

Though compulsive technology use as conceptualized herein falls just short of a behavioral addiction, it is important to understand what addiction is and how it has been studied. The World Health Organization (1989) defines addiction as the use of something for relief, comfort, or stimulation, and which often continues, in part, due to cravings when it is absent. It has also been defined as compulsive use that is not necessary, accompanied by some impairment of health or social functioning (Institute of Medicine (U.S.). Committee to Identify Strategies to Raise the Profile of Substance Abuse and Alcoholism Research., 1997a, b). A behavioral addiction involves engaging in a specific behavior for relief, comfort, or stimulation, and which results in discomfort or unease of some type when discontinued (Porter and Kakabadse, 2006).

The most comprehensive definition of technology addiction within MIS research is defined as “a psychological state of maladaptive dependency on the use of a technology to such a degree that the following typical behavioral addiction symptoms arise: (1) salience—the technology dominates a user’s thoughts and behaviors; (2) withdrawal—negative emotions arise if a person cannot use the technology; (3) conflict—the use of the technology conflicts with other tasks, which impairs normal functioning; (4) relapse and reinstatement—a user is unable to voluntarily reduce the use of the technology; (5) tolerance—a person has to use the technology to a greater extent to produce thrill; and (6) mood modification—using the technology offers thrill and relief, and results in mood changes”(Turel et al., 2011a).

While the discussion of technology addiction is not new, very little research on compulsive technology use has been done. Research from 1985 on the behavioral addiction of playing electronic games warned that this phenomenon appears to be an “instance of new technology producing an activity that has the necessary features to give it potential for excess, and catching society unawares before it can anticipate the dangers and instigate the sorts of controls that have grown up around more traditional pursuits, such as drinking alcohol or gambling”(Orford, 2005). More recent research along this stream has looked at how personality relates to the negative effects of employee technology addiction on a continuum ranging from problematic use (i.e., using a technology at inopportune times) to pathological use (i.e., inability to stop using a technology to the detriment of oneself) (Buckner V et al., 2012). Buckner et al.’s work (2012) demonstrated that in general, the five factor model of personality could predict some aspects of problematic use, but in general could not predict pathological use. Similar work viewing technology use on a continuum has also studied the addiction phenomenon ranging from pathological computing addictions on the high end to non pathological high engagement computing activities on the low end (Charlton and Danforth, 2010). It is towards this area of the technology use continuum—non pathological, yet spontaneous and automatic—which compulsive technology use is conceptualized.

Though research related to compulsive technology use exists (Meerkerk et al., 2009), there has been a consistent lack of clear terminology in research looking at this type of compelling behavior with some form of technology (Carbonell et al., 2009). A range of compulsive technology use related phenomena have been studied (see Appendix C). Examples include: information addiction (Young; Young, 1998), mobile email addiction (Turel and Serenko, 2010), problematic internet use (Davis et al., 2002), computer addiction (Charlton and Danforth, 2010; Neumann, 1998), and internet addiction (Yellowlees and Marks, 2007; Young et al., 2011). This vein of research has found that those with impulse control and addictive disorders are especially at risk for using technology in problematic ways (Mottram and Fleming, 2009).

Similar phenomena have been indentified in flow research. The theory of flow (Csikszentmihalyi, 2000) states that IT facilitates a mind state in which people are so intensely involved in an activity, that nothing else seems to matter. In this state the experience itself is so enjoyable that individuals will do it even at great cost, for the sheer sake of doing it(Csikszentmihalyi, 1988). The concept of flow is a demonstration of the kind of focused attention and stimulation that is on a continuum, from positive and enhancing to maladaptive and pathological, connected to behavioral addiction (Porter and Kakabadse, 2006).

Research has shown that compulsive behaviors often occur alongside other addictions. Alcoholics are often heavy smokers, and smokers tend to drink more coffee; heroin users frequently use various other drugs plus alcohol (Fortuna and Smelson, 2008; Shin et al., 2011). This has also been shown to be the case with workaholism and technophilia (technology addiction) in that the behavior of the workaholic serves to trigger technophiliac behaviors (Porter and Kakabadse, 2006). There is a compounding effect in that the strength of one compulsion serves to strengthen the other. This highlights why certain technology platforms can be so engaging and compelling. If a single IT platform—such as a smartphone—can facilitate and enable multiple compelling interaction (e.g., compulsive Facebook use, compulsive email use, compulsive Angry Birds use), then that particular IT platform may drive extremely high levels of use from the compulsive mobile phone user.

In summary, technology use can be viewed on a continuum from very intentionally driven use on one end, to automatically driven pathological addiction on the other end. Compulsive technology use is a type of technology use which falls just short of a pathological addiction to technology. In defining compulsive technology use, I build on the work of Ajzen and Fishbein (2000). Ajzen and Fishbein (2000) state that automatic processes meet all or most of the following criteria: "they are unintentional in the sense that no act of will is required to initiate them; they occur outside awareness; they are uncontrollable, such that a person cannot stop the process once it has started; and they are effortless or efficient in that they do not interfere with other (conscious or unconscious) cognitive processes." Adapting this definition, I define compulsive technology use as *spontaneous interaction with technology that is unintentional, uncontrollable, effortless, and efficient*.

Compulsive technology use has only recently begun to be identified by MIS researchers. Most related research has examined similar phenomena such as problematic internet use, internet addiction, and obsessive compulsive use. Compulsive technology use represents a stage of system use which is driven by something other than behavioral intent. Compulsive technology use encompasses a stage of use which has moved beyond the initial acceptance of a technology and moved beyond the intentional decision to continue using a technology (i.e., continuance). It is a type of technology use which has extended beyond the goal orientation and intentionality of technology habit. Theories which inform this type of compulsive technology behavior will be discussed in the next chapter.

CHAPTER THREE

THEORETICAL DEVELOPMENT

3.1 Theoretical Framework to Understand Compulsive Technology Use

The dominant MIS related behavioral theories such as the theory of reasoned action (TRA) (Ajzen, 1981; Ajzen and Fishbein, 1975; Ajzen and Fishbein, 2000) or the theory of planned behavior (TPB) (Ajzen, 1991) focus on technology use that is reasoned or planned. However, these theories with their focus on intentional action do not address what influences automatic, spontaneous or compulsive behaviors. Fortunately, there are several theoretical perspectives that address these type of automatic behaviors. First, I will discuss Simon's (1947) theory of automatic behavior, which provides a lens to understand compulsive technology use. Next, I will briefly review classical conditioning and operant conditioning as these theories were the dominant theories at the time of Simon's theorizing. Finally, I will use Simon's (1947) theory of automatic behavior to develop a conceptual model of compulsive technology use.

3.1.1 Theory of Automatic Behavior

Simon's (1947) seminal work on administrative behavior provides a general behavioral theory in which behaviors become automatically driven. His theory of automatic behaviors was greatly overshadowed by the dominant theory of the day—classical conditioning (Pavlov, 1927). Skinner's (1963) work on operant conditioning was the next major behavioral theory to gain ground in research dealing with automatic behaviors. However, the nuance in Simon's theory of automatic behaviors has been largely overlooked. This is partly because Simon was building a rational system view for the behavior of organizations—a theory which saw great acceptance

(Mahoney, 2005). His theory of automatic behavior was subsumed in his discussion of the cognitive limitations of rational systems. In short, his theory of automatic behavior helps inform the limits of which the rationality of organization behavior occurs (Simon, 1947). This line of theorizing was building upon the more dominant theories of the day (i.e., classical conditioning, operant conditioning). Figure 1 gives an overview of Simon's model that provides the theoretical lens for this dissertation.

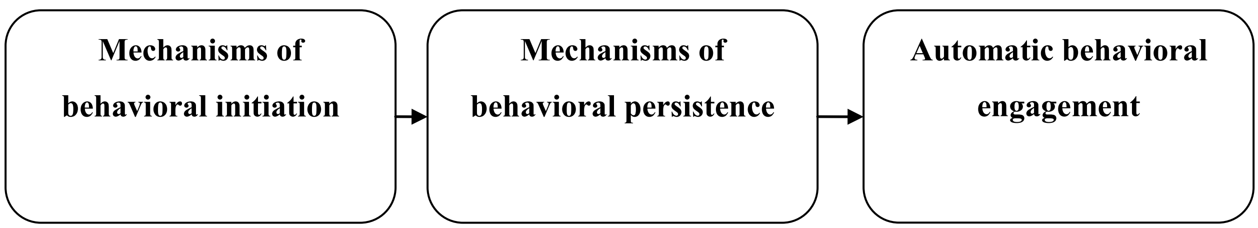

Figure 1: Conceptual Model

Classical conditioning is one of the oldest theories on automatic behavioral engagement (Saladin et al., 2006). It has served as a framework to understand how certain cues can drive behaviors (Rohsenow et al., 2001; Rohsenow et al., 1990) and is a form of learning in which neutral and unconditioned stimuli are repeatedly paired (Pavlov, 1927). After individuals are repeatedly exposed to a paired stimulus, the association between the stimulus becomes learned and the conditioned stimulus alone can elicit an automatic response (Kazdin, 2005).

Take, for example, the pairing of coffee drinking with cigarette smoking. A cup of coffee which is a neutral or unconditioned stimulus, if repeatedly paired with a cigarette by an individual who smokes while drinking coffee will result in the coffee becoming a conditioned stimulus to elicit a smoking response (Kaganoff, 2011). This will result in coffee serving as a trigger for cigarettes. In this example of classical conditioning, it is not the behavior of smoking or nicotine addiction which drives the behavior—while the cigarette itself certainly has chemical properties which serve to trigger future smoking—rather it is the association of coffee and cigarettes which has been conditioned into the individual.

The next theory on automatic behavioral engagement which rose to prominence is operant conditioning. Operant conditioning is a form of learning in which behaviors are influenced by the consequences that follow them (Skinner, 1963). Future behaviors can be influenced by several factors, such as; 1) the preceding settings or stimuli, 2) behavioral reinforcements, and 3) changes in consequences (Kazdin, 2005). The preceding settings or stimuli act as triggers which become associated with different consequences and which can influence the likelihood of a behavior. The example of coffee and cigarettes can serve to illustrate operant conditioning. The coffee, an antecedent to smoking, becomes a cue, which is associated with pleasurable consequences of smoking such as reduced anxiety and induced euphoria. This pattern of drinking coffee with a cigarette is likely to be reinforced by further positive experiences with smoking. Over time, the continued positive experience associated with cigarette smoking will reinforce the pattern of smoking cigarettes while drinking coffee (Kaganoff, 2011). A technology example would be the smartphone user who not only uses it for calls but also uses Twitter on this device. The smartphone becomes associated with the pleasurable consequences of using Twitter such as increased information and feelings of connectedness. Over time, the continued positive experience associated with Twitter will reinforce the association of smartphone use with Twitter use.

Building on classical and operant conditioning theorizing, Simon proposed a general theory of automatic behavior (Simon, 1947). Simon's theory of automatic behavior defines two principle sets of mechanisms that distinguish behavior. First, there are those mechanisms that initiate and stimulate a behavior to commence in a particular fashion. Simon calls these initiatory mechanisms the mechanisms of behavioral initiation. The mechanisms of behavioral initiation imply two things: (1) they imply that some external or environmental factor is serving to cue or trigger the behavior into motion, (2) they imply an internal sensitivity to behavioral triggers.

In applying Simon's (1947) framework, this dissertation focuses on only the first implication. This implication when taken in the context of technology use demonstrates that the external or environmental factors serving to trigger behaviors into motion can be considered elements of technology design. As such, the focus of the mechanisms of behavioral initiation will be on the elements of design. The second of Simon's (1947) implications of the mechanisms of behavioral initiation demonstrate that individuals may have an inherent dispositional sensitivity toward behavioral triggers. This implies that certain individuals who possess certain attributes will likely be more affected by elements of technology design than those who do not possess those attributes. However, identifying those specific internal sensitivities to these triggers (however interesting), is out of the scope of this dissertation.

Once the mechanisms of behavioral initiation have stimulated the behavior, the second form of behavioral mechanisms comes into play. These are psychological mechanisms, internal to the individual, which cause an initiated behavior to persist. Simon calls these the mechanisms of behavioral persistence. The mechanisms of behavioral persistence imply that once behaviors have commenced in a particular direction, strong psychological processes take over which causes the behaviors to continue in the same fashion. Simon (1947) identified two psychological mechanisms in particular which act to cause behaviors to persist. The first is habit and the second is sunk costs. Research that has expounded on Simon's theorizing has indicated as a mechanism of persistence, habit is an "important mechanism that assists in the preservation of useful behavior patterns" (Mahoney, 2005). Likewise for Simon's second mechanism of persistence, "activity often results in psychological sunk costs that make persistence of attention in the same direction advantageous"(Mahoney, 2005). Simon also noted the distinction between economic and psychological sunk costs. As such, application of Simon's theorizing should focus on those psychological, rather than economic, sunk costs.

The mechanisms of behavioral persistence serve to free the individual from the cognitive burdens associated with intentional action, and serve to automatically engage behaviors (Simon, 1947). In the context of technology use, these mechanisms of behavioral persistence are identified to be an individual's technology habit and his/her perception of sunk costs.

Figure 2 presents the research model informed by Simon's theory of automatic behavior. Table 1 presents the definitions for the proposed constructs presented in the research model. Next, I develop the concept of compulsive technology use as a form of automatic behavioral engagement in the context of technology.

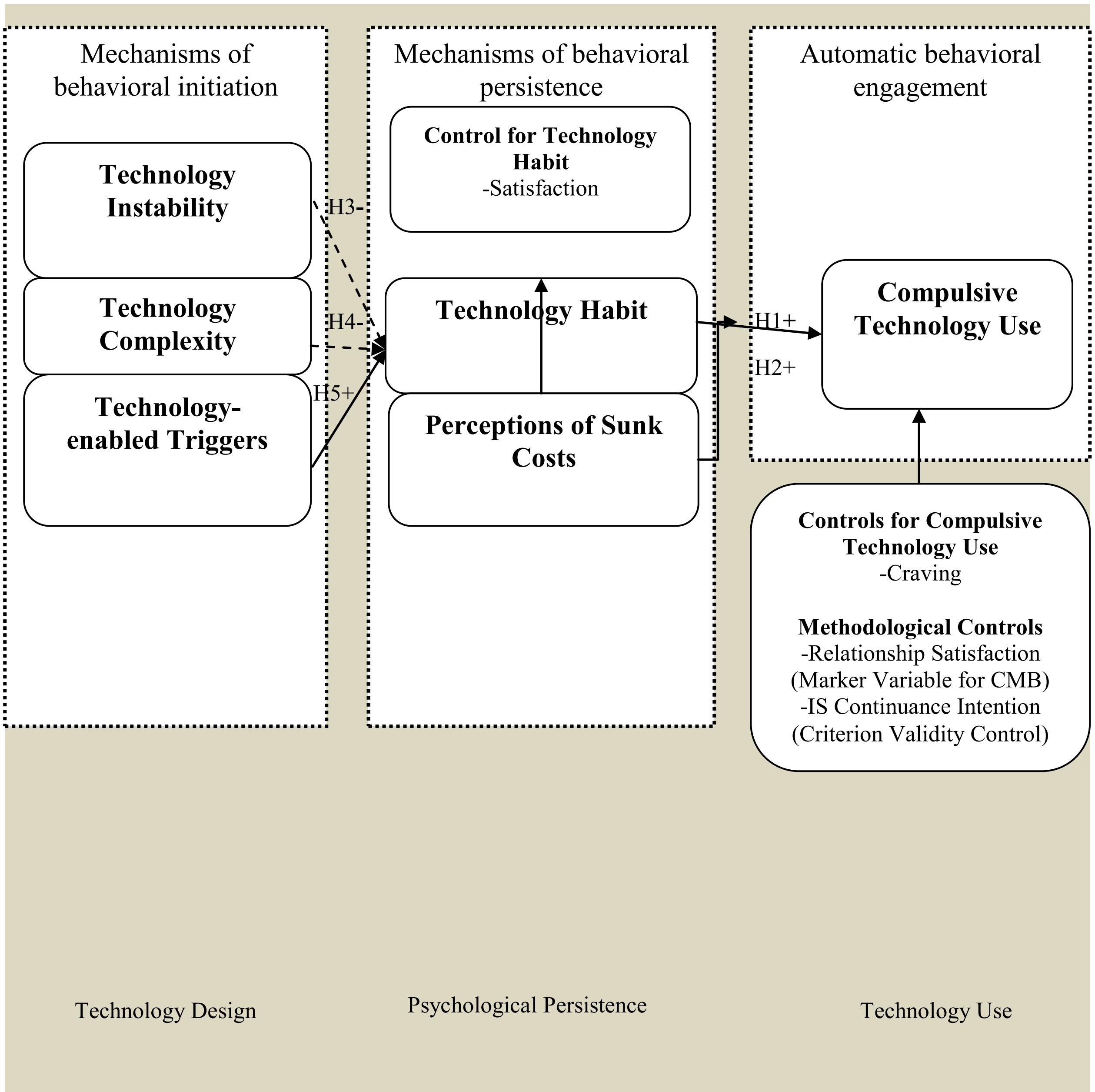

Figure 2 Research Model

Table 1: Construct Definition Table

Construct	Definition	Informing source
Compulsive Technology Use	Spontaneous interaction with technology that is unintentional, uncontrollable, effortless, and efficient	Adapted from Ajzen and Fishbein, 2000
Technology Habit	"Goal oriented behavior which we establish from previous experiences"	Polites and Karahanna, 2012
Perception of Sunk Costs	An individual's perception of a previous investment of money, time, or effort.	Adapted from Arkes and Blumer, 1985
Technology Instability	Perturbation in the structure and behavior of a technology which results in increased performance variability	Adapted from Cutcher-Gershenfeld and Rebentisch, 2003
Technology Complexity	The degree to which a technology perceived as relatively difficult to understand and use	Adapted from Thompson et al., 1991
Technology-enabled Triggers	Technology features which provide behavioral stimuli	Newly developed

3.2 Automatic Behavioral Engagement: Compulsive Technology Use

In this dissertation, I develop the notion of compulsive technology use. Compulsive technology use is a stage of system use in which behaviors are engaged in spontaneously. This research fits in the stream of research that argues that human behavior often proceeds automatically, or mindlessly, bypassing conscious reasoning altogether (Ajzen and Fishbein, 2000; Bargh et al., 1996; Fazio, 1990). I define compulsive technology use as *spontaneous interaction with technology that is unintentional, uncontrollable, effortless, and efficient*.

Compulsive technology use fits the automatic attitude-behavior sequence described by Ajzen and Fishbein (2000) in that compulsive technology use is unintentional in the sense that no act of will is required to initiate it; it occurs outside awareness; it is uncontrollable, such that a person has difficulty stopping the process once it has started; it is effortless and efficient in that it does not interfere with other conscious or unconscious cognitive processes (Ajzen and Fishbein, 2000). This spontaneous and compulsive technology use behavior taps into those aspects of doing something that is unplanned and unreasoned (de Guinea and Markus, 2009). Compulsive technology use represents a stage of system use which is driven by something other than behavioral intent. Compulsive technology use encompasses a stage of use which has moved beyond the initial acceptance of a technology and moved beyond the intentional decision to continue using a technology (i.e., continuance). This compulsively and automatically driven behavior happens without awareness, control and attention (Bayer and Campbell, 2012).

Though research related to compulsive technology use exists, there has been a consistent lack of clear terminology in research looking at behavioral addictions to some form of technology (Carbonell et al., 2009). Similar phenomena have been referred to as information addiction (Foegen, 1997), mobile email addiction (Turel and Serenko, 2010), problematic internet use (Davis et al., 2002), computer addiction (Charlton and Danforth, 2010), and Internet addiction (Yellowlees & Marks, 2007). These related phenomena are often distinguished by cognitive salience (the tendency to think about an activity to an increasingly greater extent), tolerance (spending an increasing amount of time performing an activity), and euphoria (gaining a buzz of excitement or a high from an activity) (Charlton and Danforth, 2010). However, though compulsive technology use is conceptualized as being on the same continuum as these types of addictive behaviors, it falls short of an actual pathological behavioral addiction.

3.3 Mechanisms of Behavioral Persistence

Simon described the mechanisms of behavioral persistence as largely psychological mechanisms which can be found internal to the individual (Simon, 1947). The mechanisms of behavioral persistence serve the purpose of causing behavior to continue its course once the behavior has been initiated in a particular direction. This persistence of behavior holds even when the original choice of activity was a matter of relative indifference (Mahoney, 2005).

Simon identified two reasons that behaviors tend to persist once initiated—habits, and psychological sunk costs. The first reason for persistence is the creation of routines and habits that focus attention toward its continuance and completion (Mahoney, 2005). Research has demonstrated that habits can drive behaviors towards the completion of goals (Verplanken, 2006). The second reason for persistence is that activity often results in psychological sunk costs that make persistence of behavior in the same direction advantageous (Mahoney, 2005). As Simon (1947) notes, "one important reason for behavior-persistence is that activity very often results in sunk costs of one sort or another that make persistence in the same direction advantageous" (pp. 95). In essence we become locked-into the course of action we have embarked upon. Perception of sunk costs are defined as an individual's perception of a previous investment of money, effort, or time (Arkes, 1985). As mechanisms of behavioral persistence become activated in the individual, the activity persists because of the individual's perception of sunk costs accrued as a result of engaging in this activity (Arkes and Hutzel, 2000).

In summary, by discussing the intervening organizational influences on individual behavior Simon noted that organizations and institutions encourage stable expectations. He also noted that organizations and institutions provide the general stimuli and attention directors that channel the behaviors of members of the group and provide those members with the intermediate goals that stimulate action (Mahoney, 2005). Simon's (1947) theory of automatic behaviors explains that there are certain internal and external factors that act to engage behaviors. Once behaviors are triggered there are certain psychological factors that cause behaviors to persist. Technology has the capability to serve as a mechanism of behavioral persistence. Next, I will develop the notions of technology habit, and perception of sunk costs. These psychological factors are internal to the individual and act to contribute to the behavior of interest—compulsive technology use.

3.3.1 Mechanisms of Behavioral Persistence: Technology Habit

In order to fully understand post-adoptive technology behaviors habit must be taken into account (Kim, 2009). Simon's (1947) theorizing informs that the mechanisms of behavioral persistence—those mechanisms which cause behaviors to continue along a course—are largely psychological. These mechanisms can be found internal to the individual in the form of habits. Technology habits serve the purpose of causing technology interaction behavior to continue its course once the behavior has been initiated. This persistence of habitual behavior holds even when the original choice of activity was a matter of relative indifference (Mahoney, 2005).

Technology habits have been classified by MIS researchers in two distinct ways. The first classification views habit as a prior behavior (Kim and Malhotra, 2005). The second classification views habit as the extent to which an individual believes the behavior to be automatic (Limayem et al., 2007). Habit is defined as a learned sequence of acts that have become automatic responses to specific cues, and function in obtaining certain goals or end-states (Polites and Karahanna, 2012; Verplanken and Orbell, 2003). Technology habit is defined as a goal oriented behavior which we establish from previous experiences (Polites and Karahanna, 2012). In this sense habits are still intentionally driven and purposeful in achieving our goal. Habits are intentional, planned and reasoned. However, as habits become deeply ingrained, they can be associated with behaviors that are far more automatic which occur without self-instruction (Triandis, 1971). Because of the association of deeply ingrained habits and automatic behaviors performed without conscious intention (de Guinea and Markus, 2009), high levels of technology habit should be positively associated with high levels of compulsive technology use. Formally stated,

Hypothesis 1: Technology habit will be positively associated with compulsive technology use.

3.3.2 Mechanisms of Behavioral Persistence: Perception of Sunk Costs

Behavioral persistence mechanisms are those psychological processes which cause a behavior to persist once the behavior has been initiated. Behavioral persistence mechanisms provide mechanisms through which spontaneous and automatic IS use behaviors can be sustained. Sunk cost theory provides a lens to understand the effect of irretrievable costs on a user's behavior. The sunk cost effect is manifested in a greater tendency to continue an endeavor once an investment of money, effort, or time has been made (Arkes and Blumer, 1985). The main argument presented in this theory is that the prior investment which is motivating the present decision to continue does so despite the fact that it objectively should not influence the decision. Rationally, we should not consider the previously expended money, time, or effort we have put into the use of a technology when we are considering whether or not to continue using the technology. However our perception of past expenditures with a technology have been shown to influence the future continued use of the technology (Al-Natour and Benbasat, 2009).

Furthermore as Simon (1947) noted, perception of sunk costs drive behavior non-rationally. An individual's previous "activity often results in psychological sunk costs that make persistence of attention in the same direction advantageous"(Mahoney, 2005). Building on the work of Arkes and Blumer (1985) I define perception of sunk costs as an individual's perception of a previous investment of money, time, or effort.

Our expended time and efforts (e.g., finding and building our friends on Facebook, our followers on Twitter, or our playlists on Spotify) should not influence our continued use. However, sunk cost theory suggests that this is not always the case. Research has identified that previous investments can influence future behaviors. Tiwana and Bush (2005) identified this phenomenon in their development of an expertise-sharing network continuance model. This model demonstrated that certain factors which emerge through irretrievable investments made by individual users after initial adoption influenced the user's ultimate continuance.

Our perception of the investment (actual or implied) we have made in conjunction with using a particular technology will likely influence our compulsive use of the technology once usage behaviors have been engaged. These perceptions demonstrate that we feel we have somehow contributed time, energy, resources, or efforts into the technology we are using. Because of the perception of sunk costs associated with this investment, we become compelled to continue using whatever we have sunk into this investment (Staw and Hoang, 1995; Tiwana and Bush, 2005). Next, I discuss each of the three facets of perception of sunk costs (money, time, and effort) in more detail.

3.3.2.1 Technology Monetary Investment

Technology monetary investment refers to an individual's perception of past money expenditures associated with a technology. Rationally, past monetary investments should not guide future behaviors. However, research shows that this is not always the case. Making follow up decisions based on earlier expenditures of capital is referred to as the sunk-cast fallacy (Guler, 2007).

Research on monetary investments guiding future behaviors has found that an increase in the price of a lottery ticket leads to higher evaluations of the lottery (Phillips et al., 1991). Similar research has found that higher paid basketball players get more playing time (Staw and Hoang, 1995). Laboratory studies using video games showed that an increased price associated with a particular aspect of the game lead to greater interaction with that same aspect (Friedman et al., 2007). Research on technology adoption has shown that the price of the technology affects both the initial adoption decision and subsequent continuance decisions (Bretschneider and Wittmer, 1993). This line of research has demonstrated that the higher something cost in the past, the more likely we will be committed to it in the future. This is a demonstration that past monetary expenditures can accrue increased perception of sunk costs which then influence behaviors.

3.3.2.2 Technology Effort Investment

Technology effort investment refers to an individual's perception of past effort expenditures associated with a technology. Individuals tend to consider the absolute value of effort spent on a given action when accounting for sunk costs (Garland and Newport, 1991).

This is reflected in goal literature which shows that rewards that require effort but seem attainable are motivating, while rewards which require little effort are uninspiring (Nunes and Dreze, 2006).

Rationally, our previous efforts should not be accounted for when determining our future decisions. However, research has demonstrated that pre-adoption learning efforts influence the probability of technology adoption (Åstebro, 2004). Take for example a smartphone user who decides to install a social networking mobile app on his/her phone. Rationally, the efforts put into installing, configuring, exploring and learning to operate the app should not be taken into account when the individual decides whether or not to adopt and continue to use the app. However, high perceptions of this previous technology effort investment increases the probability of future use (Åstebro, 2004). One possible explanation for this is that the individual inflates the value of the past investment (Arkes and Hutzel, 2000) a demonstration that perceived sunk costs can be a better predictor of future behavior than actual sunk costs. Expectations regarding future behaviors appear to depend on perceptions of previous efforts (Nunes and Dreze, 2006).

3.3.2.3Technology Time Investment

Technology time investment refers to an individual's perception of the amount of time associated with previous technology interaction sessions. The total amount of time and the frequency with which a technology is used has generally been equated to system success vis-à-vis system usage (Adams et al., 1992; Compeau et al., 1999). However, the time spent with a technology can also be a predictor of future use. Research on whether internet users respond to sunk time costs has demonstrated that after a particular website imposed an access charge, the remaining users stayed longer (Manley and Seltzer). Similar work found that online video game players experiencing time lags actually end up staying longer after encountering delays (Klein et al.). Because "stickier" websites earn more advertising revenue, managers of websites (e.g., Wall Street Journal website) deliberately slow the login process so users will then stay longer once logged in (Schwartz, 2001).

Research on the investment of time shows that the more time spent with an object, the higher the future evaluation of the object will be (Staw and Hoang, 1995). The frequency of past behavior is a representation of the amount of time spent engaged in the behavior (Aarts et al., 1998). A psychological time investment represents a cost that makes a future change in course much less likely (Samuelson and Zeckhauser, 1988). Research has demonstrated that when the time required to learn a system is high, individuals will be more likely to stick with the system due to increased perception of sunk costs (Polites and Karahanna, 2012).

3.3.2.4 Summary: Perception of Sunk Costs

In summary, perception of sunk costs stands as an important determinant of future behavior as a mechanism of behavioral persistence. In the context of technology, an individual's perception of sunk costs consists of three interrelated facets: 1) technology monetary investments, 2) technology effort investments, and 3) technology time investments. Perceptions of past money, effort, and time associated with a technology are referred to as perception of sunk costs. The sunk cost effect demonstrates that the perceptions of these past investments—though often inflated (Arkes and Hutzel, 2000)—will cause future behaviors to persist. Psychological sunk costs can make the persistence of a given action advantageous to the individual performing the action (Mahoney, 2005). Traditional sunk cost theory has proposed that past investments in money, effort, and time will drive future behaviors non-rationally (Arkes and Blumer, 1985). Technology has the capability to provide mechanisms of behavioral persistence in the form of perception of sunk costs.

Simon (1947) identified habit and sunk costs as two types of behavioral persistence mechanisms. Staying true to this theorizing, technology habit represents a form of psychological persistence which should positively associate with compulsive technology use. Perception of sunk costs represents a form of psychological persistence which should also positively associate with compulsive technology use. However, the mechanism by which perception of sunk costs affects compulsive technology use is more complex. High levels of perception of sunk costs indicates an individual has a high level of awareness or high level of importance associated with his/her use (especially time and effort) of a technology (Polites and Karahanna, 2012). As such, the increased evaluation of past actions should strengthen the effect of technology habit on compulsive technology use because his/her past actions are associated with current habits (Neal et al., 2006). This compounding effect between the drivers of behavioral persistence is expected to influence compulsive technology use. Formally stated,

Hypothesis 2: Perception of sunk costs will moderate the effect of technology habit on compulsive technology use such that as perception of sunk costs increases the positive relationship between technology habit and compulsive technology use becomes stronger.

3.4 Mechanisms of Behavioral Initiation

According to Simon's (1947) theory of automatic behavior, the mechanisms of behavioral initiation—mechanisms that initiate and stimulate a behavior to commence in a particular fashion—are largely external to the individual. The mechanisms of behavioral initiation imply that some external or environmental factor is serving to cue or trigger the behavior into motion (Simon, 1947).

Technology has the capability to serve as a mechanism of behavioral initiation. These initiatory mechanisms act as contextual drivers for the stronger psychological persistence mechanisms (Simon, 1947). In the context of technology, examples of these drivers include (1) the level of technology instability, (2) the level of technology complexity, and (3) the features of the technology that act to initiate behavior such as the embedded cuing mechanisms of a technology.

Next, I will further develop the mechanisms of behavioral initiation in a technology context as I more specifically discuss the mechanisms of behavioral initiation which contribute to the behavioral persistence mechanism technology habit.

3.4.1 Mechanisms of Behavioral Initiation: Technology Instability

A stable context refers to the circumstances in which a behavior is performed. Research has contended that behavior is contingent on the opportunity to perform the behavior under similar, if not identical circumstances (Aarts et al., 1997; Verplanken and Orbell, 2003). A stable context has been defined as the presence of similar situation cues and goals across more or less regularly occurring situations (Carter et al., 2011). When situational cues and relevant goals of the individual remain the same (or similar) across consecutive behavioral attempts with technology, a stable context exists (Limayem et al., 2007).

The strong association of habit and a stable context has long been acknowledged, as habits generally take substantial time to develop, and require frequent repetition of a given behavior in a stable context (Ouellette and Wood, 1998). Research has identified that the strength of habits are not only based on past behavioral frequency, but also on the stability of the performance context (Ouellette and Wood, 1998; Wood et al., 2002). However, simple repetition of a behavior in a stable context only increases the likelihood that the behavior will become habitual, making context stability an antecedent of habit, as opposed to a facet of it (Polites, 2009).

In the context of technology use behaviors, technology stability should theoretically be an important antecedent of technology habit. However, measuring the relative stability of a technology has proven difficult in extant research (e.g., Limayem et al., 2007). Though stability may be a necessary antecedent to habit, it has not proven to be sufficiently predictive. Several studies have looked at the predictive power of stability, but have been unable to flesh out the theorized effect (e.g., Wood et al., 2002; Polites, 2009). Because the phenomenon of technology stability has been difficult to observe, identifying the relative instability of a technology may be a more promising avenue of study.

Technology instability has been identified as an issue which must be considered by technology designers and sellers according to recent popular press articles. Recent market research has classified the phenomenon of app instability as an annoyance as iOS apps seem to crash more than Android apps (Geron, 2012). Several possible reasons have been identified such as hardware malfunction, software malfunction, network malfunction, language malfunction, and memory malfunction (Geron, 2012). Regardless of the source of instability or what can be done to prevent instability, mobile app users have an expectation of how apps should perform (Tudor, 2013). The common take away from this line of thought is that if apps do not perform as expected (an indication of instability in a system), individuals will likely uninstall the app.

Technology instability is defined as perturbation in the structure and behavior of a technology which results in increased performance variability (Cutcher-Gershenfeld and Rebentisch, 2003). Instability occurs when a technology responds to external stimuli in a way that makes the system less controllable and unpredictable. For example a mobile app with high levels of instability would not respond to user input as expected, as demonstrated by the app crashing or functioning improperly. Each subsequent interaction with such an app would become successively less predictable and controllable. The interaction would become unplanned and unexpected (Inkpen and Beamish, 1997). Technology instability involves both a degree of unpredictability and an increasing lack of control (Cutcher-Gershenfeld and Rebentisch, 2003). As stability has been identified in the literature as a necessary condition for habit development, high levels of instability should be associated with lower levels of habit. Formally stated,

Hypothesis 3: Technology instability will be negatively associated with technology habit.

3.4.2 Mechanisms of Behavioral Initiation: Technology Complexity

Complexity refers to how difficult a technology is to learn to use and understand. Complexity has been shown to be an important negative predictor of system use (Moore and Benbasat, 1991; Thompson et al., 1991; Venkatesh et al., 2003). Complexity is defined as the degree to which an innovation is perceived as relatively difficult to understand and use (Thompson et al., 1991). This definition is based on earlier work on complexity which looked at how complex idea innovations were slow to diffuse and be communicated across cultures

(Rogers and Shoemaker, 1971). Research has suggested that when considering the elements of technology design, it is important to consider the overall complexity as to not overwhelm users (Dennis et al., 1988).

Research has identified complexity as an important determinant of future behavior. Thompson et al., (1991) showed that technology complexity was especially predictive of system use that was voluntary in nature as more complex voluntary systems were less likely to be used. In the context of mobile app use, this would indicate that very complex apps do not promote high levels of use. Venkatesh et al., (2003) found that complexity was initially significant in predicting intentional behavior, but then became non-significant over time. In general, complexity has been shown to be negatively associated with intentional system use (Nan, 2011). It is viewed as more predictive of the earlier stages of system use—such as adoption and acceptance. As system use behavior becomes more routinized, the strength of the negative association is weakened (Venkatesh et al, 2003).

Complexity has also been shown to be an important negative predictor of habit (Lankton et al., 2010). This research showed that task complexity had a significant negative effect on habit. Other research on habit has shown that habitual behaviors are less complex than intentional behaviors (Wood et al., 2002). Similar research has shown that significantly stronger habits emerge from simpler tasks rather than more complex tasks (Verplanken, 2006; Verplanken and Orbell, 2003). This is a demonstration that very complex tasks inhibit strong habit formation. This shows that the more complex a system is the less likely habits will form. Likewise, high levels of technology complexity should be associated with weaker technology habits. Formally stated,

Hypothesis 4: Technology complexity will be negatively associated with technology habit.

3.4.3 Mechanisms of Behavioral Initiation: Technology-enabled Triggers

Most classic behavioral theories point to the importance of an external stimulus to initiate action. Hull's Stimulus Response Theory (1943) and other theories of classical conditioning suggest that all behaviors must first be primed or cued before the behavior can be engaged. Technology can provide the necessary external priming stimuli in the form of technology-enabled triggers. Technology-enabled triggers are defined as technology features which provide behavioral stimuli. These technology features serve as external behavioral initiation mechanisms, or triggers which set behaviors into motion (Simon, 1958).

These technology-enabled triggers can present themselves in a number of forms. Take for example today's smart phone device. The design features of smart phones includes: a variety of indicator lights of varying colors, and flashes of varying intensity; an innumerable combination of vibration sequences, visual alerts, symbols, or messages; a variety of audible sounds, beeps, tones and rings. All serve the purpose of signaling to their human operator, "Hey…I have something for you… Look at me… Listen to me… Pick me up… Interact with me." This has important implications for the design of a technology as technology-enabled triggers can be purposefully incorporated into a system to act as mechanisms of behavioral initiation. This point is reflected in calls for information systems research that is design science oriented as the design of a system can influence the use of the system (Hevner, March, Park and Ram, 2004). Once the behavior is primed and initiated there are psychological processes which provide guidance and persistence for the action.

More recent research building on incentive conditioning suggests that when behavioral triggers are associated with a rewarded response, the value associated with the reward becomes ingrained and conditioned into the triggers themselves. (Neal et al., 2006) Thus as the behavior is subsequently performed the triggers themselves begin to carry value enough to motivate action in the form of craving (Kavanagh et al., 2009). The behavior is driven because the past reward conditioning has established the necessary cognitive context-response associations, and the context becomes embedded with the motivational force for responding (Wood et al., 2002).

An information system or technology can serve as the context for individuals to perform a variety of behaviors. Research on smartphone use shows that automatic checking behaviors emerge and are reinforced by the quickly accessible informational rewards provided by the smartphone (Oulasvirta et al., 2012). The more an individual's technology use behaviors can be primed and triggered through the design of a system, the more likely the individual is to have interacted with the system. As such, high levels of system interaction should be associated with high levels of habit. This suggests that technology-enabled triggers will be positively associated with technology habit. If a technology can provide sufficient technology-enabled triggers then people interacting with that technology should have stronger habits. Formally stated,

Hypothesis 5: Technology-enabled triggers will be positively associated with technology habit.

In summary, Simon's (1947) theorizing surmises that behaviors can become automatically engaged and enacted without conscious intention. His framework can be applied to the context of technology usage behaviors which occur automatically and spontaneously. In the context of technology, compulsive technology use has been identified as this type of automatically engaged behavior. Simon's theory describes how mechanisms of behavioral engagement serve the purpose of initiating a behavior in a particular direction. Once behaviors are engaged, there are mechanisms of behavioral persistence which act to drive the behavior and cause it to persist. Table 2 provides a summary of the research model hypotheses.

Table 2: Research Model Hypotheses

Research Model Hypotheses	
H1	Technology habit will be positively associated with compulsive technology use
H2	Perception of sunk costs will moderate the effect of technology habit on compulsive technology use such that as perception of sunk costs increases the positive relationship between technology habit and compulsive technology use becomes stronger
H3	Technology instability will be negatively associated with technology habit
H4	Technology complexity will be negatively associated with technology habit
H5	Technology-enabled triggers will be positively associated with technology habit

CHAPTER FOUR

RESEARCH METHODOLOGY

4.1 Research Design

For several reasons, this dissertation uses a survey research design. First, a survey design provides a way to tap into the perceptual variables of interest of this dissertation. These perceptual constructs are thereby quantified so that comparisons can be made and inferences can be drawn about the relationships between the variables in the population. Previous research on psychological constructs such as IS habit has used survey items to begin to assess behaviors that are not easily observable (e.g., Polites and Karahanna, 2012). .

Second, a survey design provides the advantage of identifying attributes of a large population from a subset of individuals (Fowler Jr, 2008). The main purpose of a survey is to generalize from a sample to a population so that inferences can be made about some behavior (Babbie, 1990); in this case compulsive technology use. Therefore, this dissertation will be able to sample a subset of the population to learn more about what drives compulsive technology use in the greater population. As compulsive technology use is a behavior that individuals perform in a variety of settings with their personal technology devices, a controlled experiment could prove unwieldy in accurately capturing the phenomenon. Therefore it would be difficult to make inferences about the population based on an experiment which does not accurately reflect the phenomenon of compulsive technology use.

Third, a survey design allows for standardized measurement that is consistent across all respondents to ensure that comparable information is obtained. Meaningful statistics are desired to examine the extent to which variability in the drivers of compulsive technology use account for variability in compulsive technology use. Without such standardized measurement, meaningful statistics cannot be produced (Fowler, 2002), and any relatedness present between the variables of interest in a given individual would not be comparable to those of another individual.

4.1.1 Sample Size

The survey research design consists of constructing and administering a questionnaire consisting of measures reflecting the intended constructs. The survey is cross-sectional in nature and scores for the independent variables and dependent variables are collected in the same survey. Scores on the measures are used to infer how the proposed constructs are related in the population. Before testing the hypotheses for the cross-sectional survey research design, there were several things which I first considered.

The first consideration was the representativeness and the size of the intended sample. The sample was a convenience sample of users of target mobile applications—specifically Facebook and Twitter. Respondents provided scores on the perceptual measures for the constructs of interest in one of these settings. The sample size needed to be sufficiently large to have the power to correctly detect an effect if there was indeed one to be detected. In determining an appropriate sample size, I followed the a priori sample size rules suggested by previous IS researchers (Marcoulides and Saunders, 2006) . Ten cases per predictor at a minimum are suggested, whereby the overall sample size is 10 times the largest of two possibilities: 1) the block with the largest number of indicators (measurement equation), or 2) the dependent variable with the largest number of independent variables impacting it (structural equation). Using these guidelines I determined the overall sample size had to be at least larger than 110 (as the scale for compulsive technology use contained 11 items).

4.1.2 Construct Development

The second item I took into consideration before testing was construct development. Before engaging in the development of construct measures, I made sure the constructs were all tightly defined.

The construct *compulsive technology use* is a newly conceptualized construct and is defined as spontaneous interaction with technology that is unintentional, uncontrollable, effortless, and efficient.

The construct *technology habit* is defined as "goal oriented behavior which we establish from previous experiences" (Polites and Karahanna, 2012).

The construct *perception of sunk cost* is a newly conceptualized construct and is defined as an individual's perception of a previous investment of money, time, or effort (Arkes and Blumer, 1985).

The construct *technology instability* is a newly conceptualized construct and is defined as perturbation in the structure and behavior of a technology which results in increased performance variability (Cutcher-Gershenfeld and Rebentisch, 2003).

The construct *technology complexity* is defined as the degree to which a technology is perceived as relatively difficult to understand and use (Thompson et al., 1991).

The construct *technology–enabled triggers* is a newly conceptualized construct and is defined as technology features which provide behavioral stimuli.

When possible, measures were adapted from existing measures. Technology habit and technology complexity are constructs which come from existing literature. As such, measures for these constructs were taken directly from previous studies and adapted to this dissertation. New constructs were developed through an iterative process of specifying the construct domain and writing items that tap into the various aspects of the domain. Specifying the domain of each variable was guided by the relevant research and theories of each respective construct. A minimum of 10 (maximum of 20) items per construct were generated and revised in an iterative process. All newly generated items were scored on a 7-point likert type scale ranging from strongly disagree (1) to strongly agree (7).

The measures were then examined with the assistance of a content area expert to help determine the content validity. This expert was a senior faculty member who has previously published research in this domain. Items that were judged to insufficiently tap into the domain of the construct were then removed or modified. This process was then repeated until the finalized measurement instrument was produced.

After all items had been finalized with the content area expert, two fellow doctoral students were recruited to examine all of the newly developed measures and sort the items into groups according to the labels provided. The results from the doctoral students were identical in that all items were sorted into their appropriate category with no assistance.

4.1.2.1 Pilot Study Pretest

Before full data collection, a pilot study was conducted in an effort to further refine the survey instrument. This was done with the overall objective of detecting any potential problems with the newly developed scales. The primary goal in the pilot study was the refinement of or removal of individual items (e.g., poorly worded, redundant, confusing, misleading) to achieve a more parsimonious final survey instrument. Undergraduate business students from a large southeastern university in the United States were invited to take part of the study. Students were incentivized to participate by entering them into a random drawing for one of five gift cards worth five dollars. Participation was completely voluntary as was entering into the drawing for the gift cards. The total number invited to complete the paper based survey was 105. Of those 105 invited, 85 agreed to participate and completed the survey; including 45 females and 40 males. No other demographic data was collected. Respondents were allowed to write in any voluntary use mobile application they used the most frequently as the focal technology for the survey. The top two voluntary apps were Facebook (N = 40), and Twitter (N=10). Respondents then answered survey questions about their use of the focal technology they wrote in.

The paper surveys were then collected and coded into SPSS to be analyzed. A complete factor analysis (including the new scales and previously validated scales) was then conducted. Before removal of any single item due to poor performance or high cross-loading, the item was manually checked against the construct definition to ensure that important facets of a construct domain were not removed. Several items were very redundant. Redundancy in a scale can create an artificially inflated Cronbach's alpha (CA) and inflated construct reliability (CR). This redundancy was removed by keeping only the best performing (measure with the highest loading) of the redundant items. This process of construct refinement was an iterative process done one step at a time. After an item was removed from the factor analysis, a new factor analysis was conducted. After the total refinement process was completed, every scale was manually compared to its intended construct definition. The resulting measures formed the final survey instrument to be used in full data collection.

4.1.3 Construct Validity

The third concept I took into consideration before testing was construct validity. Construct validity was assessed first by conducting a confirmatory factor analysis of the measures and looking at the pattern of correlations. Convergent validity was assessed by examining how scores on the independent variables relate to scores on a construct that theory suggests they should be related to, such as satisfaction. For this a perceptual measure for satisfaction was included on the survey instrument. Discriminant validity was assessed by comparing scores on the variables of interest with scores on a variable that theory suggests should not be related to such as partner/spouse relationship satisfaction. A perceptual measure for this variable was included in the survey. The specifics of these analyses are further addressed in the analysis section.

4.1.4 Reliability Assessment

The fourth concept I took into consideration was reliability. Reliability was assessed to determine the accuracy and consistency of the scores. I used a correlation based approach to determine internal consistency reliability (Cronbach's alpha) as well as the PLS method to generate construct reliabilities (CR). In general, both approaches are a function of the average correlation to the number of items. Scores above .70 were the minimum standard to gauge these measures. I took into consideration that alpha can be high despite lower item correlations or multidimensionality. I also took into account that using alpha to determine reliability only covers random response error or item specific error. More specifics on these approaches are covered in the analysis section.

Previously validated measures were used where possible for the model's latent variables of interest. These include: Habit (Limayem & Hirt, 2003; Limayem et al., 2007), and Complexity (Venkatesh et al., 2003). Previously validated scales were also used for control the measures of Satisfaction and IS Continuance Intention (Bhattacherjee, 2001). Newly developed items will be used for the following constructs: Compulsive Technology Use, Perception of Sunk Costs, Technology Instability, and Technology-enabled triggers. New measures were also developed for the controls Craving and Relationship Satisfaction.

4.1.5 Method Variance

A limitation to this overall research method is that cross-sectional surveys are subject to common method variance. Method variance is defined as variability that is due to the method by which the data are collected rather than to the variables of interest themselves. Method variance can either inflate the relationship (when both constructs are subject to the same method factor) or deflate the relationship (when one construct is subject to one method factor and the other is subject to a different method factor). Given the cross-sectional nature of a convenience sample, it is likely that common method bias may be an issue for my research design.

To help control for common method variance, and assess the extent to which it affects my results, I included a marker variable as suggested by Malhotra, Kim and Patil (2006). I included the marker variable of partner/spouse relationship satisfaction. Relationship satisfaction should have no expected correlation the variables of interest, thus any correlation can be attributable to common method. The marker variable can then be used to calculate the extent to which my results are the result of common method bias. More specifics of this approach are found in the analysis section. Next, I will discuss the specific measurement domain of each construct for the research model.

4.2 Compulsive Technology Use

Compulsive technology use is defined as a spontaneous interaction with technology that is unintentional, uncontrollable, effortless, and efficient. Compulsive technology use has only recently begun to be identified by MIS researchers. Using the conceptualization of compulsive technology use as previously discussed, new items were generated for this measure.

Items all tap into various aspects of the automatic attitude-behaviors sequence described by Ajzen and Fishbein (2000) in that it is behavior that 1) occurs without awareness, 2) is difficult to control, 3) is effortless and efficient, and 4) is unintentional in the sense that no act of will is required to initiate it. A total of seven items were developed for the measure of compulsive technology use. Items were scored on a 7-point Likert type scale ranging from strongly agree (1) to strongly disagree (7). Table 3 contains the items for this measure.

Table 3: Compulsive Technology Use Items

Compulsive Technology Use- Spontaneous interaction with technology that is unintentional, uncontrollable, effortless, and efficient.	
Measure	**Source**
I choose this app without even being aware of making the choice	Newly developed
I unconsciously start using this app	
Using this app is something I do without even being aware of it	
I find myself checking in with this app without explicitly planning to do so	
I often feel compelled to use this app	
I often feel I spontaneously use this app	
I feel I must use this app	

4.3 Technology Habit

Technology habit is defined as a goal oriented behavior which we establish from previous experiences (Polites and Karahanna, 2012). Previously validated measures for technology habit (Limayem et al., 2007) were used. A total of four items were adapted for the measure of technology habit. Items were scored on a 7-point Likert type scale ranging from strongly agree (1) to strongly disagree (7). Table 3 contains the items adapted from Limayem et al.'s (2007) measure for habit.

Table 4: Technology Habit Items

Technology Habit- Goal oriented behavior which we establish from previous experiences (Polites and Karahanna, 2012).	
Measure	**Source**
The use of this app has become a habit for me	Adapted from Limayem et al., 2007
I don't even think twice before using this app	
Using this app has become natural to me	
Using this app has become automatic to me	

4.4 Perception of Sunk Costs

Perception of sunk costs refer to an individual's perception of a previous investment of money, time, or effort (Arkes and Blumer, 1985) associated with a particular technology. Items were generated which reflect the sunk costs associated with the use of technology. A total of ten items were developed for the measure of perception of sunk costs. Items were scored on a 7-point Likert type scale ranging from strongly agree (1) to strongly disagree (7). Table 4 contains the newly developed items.

Table 5: Perception of Sunk Costs Items

Perception of Sunk Costs – An individual's perception of a previous investment of money, time, or effort (adapted from Arkes and Blumer, 1985)	
Measure	**Source**
I feel I have invested considerable time using this app	Newly developed
I have put a lot into my use of this app	
I have invested a great deal of effort into using this app	
I feel I have spent a great deal of energy using this app	
I feel I have put considerable effort into using this app	
I feel invested in this app	
I am aware of how much money I have spent on this app	
The money I have spent on this app was a good investment	
I am satisfied with the amount I paid for this app	
The money I paid for this app was well worth it	

4.5 Technology Instability

Technology instability is defined as perturbation in the structure and behavior of a technology which results in increased performance variability (Cutcher-Gershenfeld and Rebentisch, 2003). Technology instability involves both a degree of unpredictability and an increasing lack of control. New measures were developed and used to measure technology stability. A total of five items were developed for the measure of technology instability. Items were scored using a 7-point Likert type scale ranging from strongly agree (1) to strongly disagree (7). Table 6 contains the items for the measure.

Table 6: Technology Instability Items

Technology Instability - Perturbation in the structure and behavior of a technology which results in increased performance variability.	
Measure	**Source**
This technology is unstable	Newly Developed
This technology has to update frequently	
I often cannot get this technology to work properly	
This technology behaves in unpredictable ways	
This technology tends to be unreliable	

4.6 Technology Complexity

Complexity is defined as the degree to which a technology is perceived as relatively difficult to understand and use (Thompson et al., 1991). In general, complexity has been shown to negatively associate with intentional system use (Nan, 2011). Complexity refers to how difficult a technology is to learn to use and understand.

Previously validated scales (Thompson et al., 1991) to measure complexity were used. A total of four items were adapted for the measure of technology complexity. Items were scored using a 7-point Likert type scale ranging from strongly agree (1) to strongly disagree (7). Table 7 contains the items for this measure.

Table 7: Technology Complexity Items

Technology Complexity - The degree to which a technology is perceived as relatively difficult to understand and use.	
Measure	**Source**
Using this app takes too much time from my normal activities	Adapted from Thompson et al., 1991
Working with this app is so complicated, it is difficult to understand what is going on	
Using this app involves too much time doing mechanical operations (e.g., data input)	
It takes too long to learn how to use this app to make it worth the effort	

4.7 Technology-enabled Triggers

All behaviors must first be primed or cued before the behavior can be engaged (Hull, 1943). Technology can provide the necessary external priming stimuli in the form of technology-enabled triggers. Technology-enabled triggers are defined as technology features which provide behavioral stimuli. However, extant research has yet to measure technology-enabled triggers. Therefore, new items were generated which tap into features of the technology which serve to prime and trigger behavioral interaction. A total of six items were developed for the measure of technology-enabled triggers. Items were scored using a 7-point Likert type scale ranging from strongly agree (1) to strongly disagree (7). Table 8 contains the items for this measure.

Table 8: Technology-enabled Triggers Items

Technology-enabled Triggers - Technology features which provide behavioral stimuli.	
Measure	**Source**
This app lets me know when there is information for me	Newly developed
This app can prompt me to use it	
This app has audible indicators	
This app has visual indicators which can alert me	
This app can vibrate when it has information for me	
This app can send me alerts	

4.8 Control Measures, Survey Demographics

Several control measures were included in the research survey. There are controls stemming from research related to the exogenous variables in the model as well as methodological controls. The first control measure which stems from research related to the dependent variable compulsive technology use comes from research related to a similar phenomenon. This control measure captures the phenomenon of craving. To date, very little research has looked at the cravings individuals may experience for certain technologies. Current research has difficulty explaining why some individuals have difficulty controlling their addictive behaviors while others do not (Abrams, 2000), primarily because they have not taken technology craving into account. Accounting for technology craving in models of technology use is important as craving has the potential to moderate addictive and compulsive behaviors (Abrams, 2000; García-Rodríguez et al., 2011).

Craving has been defined as a subjective experience within one's awareness that reflects retrieval from the memory systems of a strong learned desire to satisfy an actual or perceived need (Kozlowski & Wilkinson, 1987). Craving is generally viewed as an intense desire or urge to obtain an appetitive target (Kavanagh et al., 2009). When an individual experiences a craving episode, spontaneous and intrusive thoughts about wanting or needing a desired object are triggered by processes outside of the individual's awareness. These intrusive thoughts are associated with a sense of anticipation for pleasure, stimulus or relief (Kavanagh et al., 2009).

Research on craving has examined the role craving plays in influencing addictive and compulsive behaviors (Abrams, 2000). This research highlighted that correctly conceptualizing craving would be useful in understanding why some individuals under certain circumstances have difficulty controlling their behaviors, while others do not. Because craving has the potential to influence compulsive behaviors (Abrams, 2000; García-Rodríguez et al., 2011), a control for craving was included in the model. A total of four items were developed for the measure of craving. Table 9 contains the items for this measure.

Table 9: Craving Items

Craving - An intense desire or urge to obtain an appetitive target (Kavanagh et al., 2009).	
Measure	**Source**
I often spontaneously think about this app	Newly developed
I sometimes feel an urge to use this app	
I find myself thinking about this app	
I have experienced feelings of craving associated with my use of the app	

The second control measure that was included is a control for the exogenous variable Technology Habit. Previous habit research has identified that the satisfaction a person feels for a technology can be an important determinant of the person's habits (Limayem et al., 2007). Satisfaction is defined as the extent to which the user of a technology feels his expectations have been confirmed (Venkatesh et al., 2003). When satisfaction causes people to continue using a technology they have previously used, there is likely to be an increase in habit formation (Lankton et al., 2010). Similar to other studies that have controlled for the effect of satisfaction on a person's behavior with technology (e.g., Tiwana and Bush, 2005), a measure for Satisfaction was included to control for this effect. A total of four items were adapted for the measure of satisfaction. Table 10 contains the items for this measure.

Table 10: Satisfaction Items

Satisfaction – The extent to which a user of a technology feels his expectations have been confirmed (adapted from Venkatesh et al., 2003)	
Measure	**Source**
How do you feel about your overall experience using this mobile app?	Adapted from Venkatesh et al., 2003
Very Dissatisfied----------------Very Satisfied	
Very Displeased-----------------Very Pleased	
Very Frustrated------------------Very Contended	
Absolutely Terrible--------------Absolutely Delighted	

I also used several methodological control variables in the study. First, a control for common method bias using a marker variable was included (Malhotra et al., 2006). This was a single item measure which assessed the extent to which the person taking the survey was satisfied with their current relationship. This item used a 7 point Likert-type scale ranging from strongly disagree (1) to strongly agree (7). The exact wording for this measure was "I am currently satisfied with my relationship with my significant other." This marker variable should theoretically not correlate with any other item in the survey.

Second, a control measure to assess criterion validity was included. The criterion variable IS Continuance Intention was chosen as many of the independent variables in the model should theoretically correlate with this latent variable. Measures for the alternative exogenous variable IS continuance intention are only used to help assess the criterion validity of the endogenous variables. The resulting latent variable was not used as an active control in the model which tested the hypotheses. A total of three items were adapted for the measure of IS continuance intention. Table 11 contains the items for this measure.

Table 11: IS Continuance Intention Items

IS Continuance Intention – a series of intentional decisions to continue using a technology (adapted from Bhattacherjee, 2001)	
Measure	**Source**
My intentions are to continue using this app rather than use any alternative technology	Adapted from Bhattacherjee, 2001
I intent to continue using this app rather than use any alternative technology	
If I could, I would like to continue my use of this app	

Demographic questions were also included in the survey. These include age, gender, highest educational level attained and university GPA.

4.9 Data Collection

Full data collection was via a web-based survey. I used FSU's version of Qualtrics to prepare, distribute and collect the data. Participants were invited through email to take part in the study. The email invitation informed participants that they were invited to take part in a research study about how people interact with voluntary use applications. They were informed that for their participation they had the option to enter into a drawing for one of ten $5.00 Starbucks gift cards. Participants were informed that the study would have no direct benefits to them and that the risks of participation would be minimal. Participants that were invited to take the survey were provided with an online link to the survey. The link took the participants to FSU's Qualtrics website which hosted the survey. Respondents were informed that their participation was completely voluntary and that all responses were anonymous. All respondents viewed an FSU statement of consent which further outlined the voluntary nature of the study, its associated risks and benefits, and ensured the anonymity of responses. Each participant that agreed to consent was assigned a unique identifier. IP addresses of the respondents were also scanned to ensure no duplication of survey takers. Once participants began the survey, an automatic timer was started. Survey's that remained incomplete after 24 hours were automatically deleted. When data collection ended, the random drawing for the Starbuck's gift cards occurred and the gift cards were sent to the winners.

4.10 Summary

In summary, this chapter presented the research methodology for this dissertation. In the next chapter I will present the results of the study.

CHAPTER FIVE

RESULTS

5.1 Introduction

In this chapter, I will describe the results of the data collection, how it was tested, and the reasoning behind the chosen analyses. I will report the findings from my analyses of the measurement model and the structural model. Then, I will report on the results of the hypothesis testing.

5.2 Participants

The target sample for full data collection was a wide range of individuals that have experience interacting with Facebook and Twitter. I used a convenience sample of undergraduate and graduate university students from a large southeastern university in the United States.

Table 12: Total Respondents Invited

Major	N	Percent
MIS	29	4.65%
Accounting	105	16.85%
Management	34	5.45%
Education	20	3.21%
Library Science	35	5.61%
Marketing	400	64.20%
Total Responses	443	71.10%

623 Students were invited from a variety of majors across the university: 1) MIS (29 students), 2) Accounting (105 students), 3) Management (34 students), 4) Education (20

students), 5) Library Science (35 students), 6) Marketing (400 students). 443 of the invited students (response rate = 0.71) completed the survey including 190 males and 248 females (See table 11). Five respondents did not identify as either male or female. The average age score of the respondents was 2.4 (with a score of 2 = “18-21 years old”, and 3 = “22-25 years old”).

Table 13: Age of Respondents

Age Range	N	Percent
< 18	1	0.22%
18 – 21	320	72.23%
22 – 25	78	17.60%
26 -34	21	4.7%
35 – 45	7	1.58%
> 45	7	1.58%

The average GPA score of the respondents was 5.9 (with a score of 6 = GPA of “3.0-3.49”).

Table 14: University GPA

GPA	N	Percent
< 1.0	0	0%
1.0 - 1.49	0	0%
1.5 - 1.99	1	0.22%
2.0 - 2.49	19	4.28%
2.5 - 2.99	86	19.41%
3.0 - 3.49	214	48.3%
3.5 - 4.0	123	27.76%

The average respondent score for level of education attained was 3.6 (with 3 = “some college”, and 4= “associates degree”).

Table 15: Level of Education Attained

Education Level	N	Percent
Some High School	0	0
High School Degree	29	6.54%
Some College	196	44.24%
Associates Degree	149	33.63%
Bachelors Degree	60	13.54%
Masters Degree	7	1.58%
Doctorate Degree	2	0.45%

Even though the response rate was around 71%, I wanted to check for non-response bias to further ensure external validity. Non-response error occurs when survey respondents are systematically different from non-respondents with respect to "one or more known or unknown characteristics" (Sivo et al., 2006). The main concern is that any finding that can be drawn from the group of participants sampled might not hold with other non-participants. This non-response bias can therefore be a threat to any external validity.

To ensure non-response bias is not a concern with this study I employed the linear extrapolation method suggested by Sivo et al., (2006) to compare the differences between early and late respondents. To do this I examined the first 50 respondents and the last 50 respondents. Then I did individual t-tests on the means of compulsive technology use (t = .68, sig. = .49), technology habit (t = 0.38, sig. = 0.70), perception of sunk costs (t = 0.67, sig. = 0.50), technology instability (t = 1.17, sig. = 0.24), technology complexity (t = 0.94, sig. = 0.35), and technology-enabled triggers (t = 0.34, sig. = 0.73. This method does not completely eliminate the possibility of a systematic bias; however, the results indicate that there is little concern that non-respondents exhibit any particular characteristics that would introduce bias into the study (Shaw, 2002).

5.3 Analysis Method: Partial Least Squares Structural Equation Modeling

A partial least squares – structural equation modeling (PLS – SEM) approach was utilized to test the measurement and structural model. The primary objective in using this approach is maximizing the total explained variance in the dependent variables while evaluating the data quality as determined by the measurement model characteristics (Hair et al., 2011). Compared to covariance based – structural equation modeling (CB – SEM), PLS is preferred for theory building and more complex models which identify key “driver” constructs, and which may contain moderator variables (Chin et al., 2003). CB – SEM attempts to minimize the discrepancy between the sample data and the proposed model, whereas PLS – SEM focuses on maximizing the variance in the dependent variables which is explained by the independent variables (i.e., minimizing error) (Chin et al., 1996). Both PLS – SEM and CB – SEM are able to consistently perform well under conditions of normality with large sample sizes; however, PLS – SEM is more robust under conditions of non-normality with smaller sample and effect sizes and is thus preferable (Marcoulides et al., 2009). The PLS-SEM assessment for this dissertation employed the two-step process suggested by Hair et al. (2011) which first examines the measures’ reliability and validity according to reflective measurement model specification or factorial validity assessment (Gefen and Straub, 2005), followed by evaluation of the structural model estimates.

5.4 Testing for Method Bias

When self-reported data are collected from a single survey at one point in time, bias may be introduced which has the potential to inflate the correlations between the variables in the study (Spector, 2006). This is known as common method bias. Recent research has indicated that research within the IS discipline tends to be more robust against common method bias as IS constructs such as satisfaction and use of a technology are generally less abstract (Malhotra et al., 2006). Malhotra et al. (2006) conducted a meta-analysis on 216 past IS studies and found that bias introduced by a common method generally only inflated correlations by 0.1 or less, and most significant relationships remained significant after controlling for common method bias.

During the design and administration of the questionnaire, I employed several best practices (Podsakoff et al., 2003) in an attempt to reduce effects resulting from a common method. First, during the design of the questionnaire independent and dependent variables were separated in an attempt to achieve psychological and proximal separation. Second, before respondents were administered the survey, they were informed multiple times that the survey is completely anonymous and that there are no correct or incorrect answers. By ensuring the anonymity of the respondents, evaluation apprehension can be reduced (MacKenzie et al., 2011).

Next, I employed two post-hoc statistical techniques as suggested by current IS researchers (Liang et al., 2007) to analyze the potential bias introduced due to the common method. The first statistical technique conducted to mitigate the threat of common method bias was the Harmon one-factor test (Podsakoff et al., 2003). I conducted this test by entering all the independent variables and dependent variables in an exploratory factor analysis (EFA). This analysis showed that a single factor did not account for a large percentage of the variance in the resulting factors as the first factor only accounted for 10.61 percent of the total variance. The complete set of items retained in the factor analysis accounted for 81.35 percent of the total variance (see table 16). This test provides additional assurance that the results are not due to common method bias (Tiwana and Keil, 2007).

Table 16: Total Variance Explained

Harmon's One-Factor Test: Total Variance Explained						
Component	Initial Eigenvalues			Rotation sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	10.78	28.36	28.36	4.03	10.61	10.61
2	5.18	13.64	42.01	3.92	10.32	20.93
3	2.76	7.27	49.28	3.36	8.84	29.77
4	2.53	6.65	55.94	3.30	8.69	38.47
5	2.24	5.90	61.84	3.18	8.36	46.84
6	1.87	4.93	66.78	2.86	7.53	54.37
7	1.72	4.53	71.31	2.75	7.24	61.62
8	1.37	3.61	74.93	2.65	6.99	68.61
9	1.30	3.44	78.37	2.55	6.72	75.34
10	1.13	2.97	81.35	2.28	6.01	81.35
11	.58	1.53	82.88			

The second statistical technique I used to mitigate the threat of common method bias was the common method variance control technique using PLS as suggested authors (Liang et al., 2007). As suggested by Malhotra, Kim and Patil (2006), during the design of the survey a marker variable—a variable which should theoretically not be highly correlated with any other variable in the study—which assessed marital/relationship satisfaction was included. I used this marker variable to assess the extent to which it relates to all other variables in the model.

The analysis showed that all paths with the marker variable were very weak and non-significant and that the variance explained by the marker variable was much less than the variance explained by the original model factors. As such, common method bias does not appear to be a significant threat to the validity of the results of this dissertation.

5.5 Testing the Measurement Model

Before testing the structural model, I assessed the construct dimensionality of the measures and the factorial validity of the latent constructs. This was done in two phases. The first phase consisted of a principle components analysis (PCA) using SPSS to rigorously analyze construct dimensionality as it cannot be measured directly with PLS but is assumed to be there a priori (Gefen, 2003; Gerbing and Anderson, 1988). The second phase consisted of using Smart PLS to assess two elements of factorial validity—convergent validity and discriminant validity—as suggested by authors (Gefen and Straub, 2005). These two elements are critical components of construct validity (Straub et al., 2004).

Before conducting the PCA, the dataset was split into groups based on which particular technology the individual used to respond to the questionnaire. Results showed that 306 respondents chose Facebook as their target technology and 136 chose Twitter as their target technology. Then I performed independent sample tests to assess both Levene's Test for Equality of Variances and a T-test for Equality of Means for the groups. Leven's test assesses the homoscedasticity assumption (Parra-Frutos, 2009) that the variances between the Facebook and Twitter groups are equal. As desired, the P-values for the tests were all well above .05 meaning that the null hypothesis of equal variances between the groups cannot be rejected. Likewise, results of the T-tests showed that the assumption of the equality of mean scores between the groups does not significantly differ from the Facebook group and the Twitter group. Thus, the PCA and all subsequent analyses can be performed on the full data set.

To conduct the principle components analysis, all items from the measurement model were included in a full data set factor analysis using a Varimax rotation with Kaiser Normalization. Extraction was based on Eigenvalues above 1.0 and descriptive statics were produced. The number of components extracted with eigenvalues above 1.0 matched the number of intended constructs (see table 15). Examination of the scree plot reflected this trend as well.

Analysis of the descriptive statistics including means and standard deviations revealed no large variance differences between items in groups.

Next, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and the Bartlett's test of sphericity were analyzed. Results for KMO indicated adequate sample size at .90 which is above the .60 suggested rule-of-thumb threshold. The Chi-square value for Bartlett's test was very large (14688.46) and significant (<.001) meaning the correlation matrix is not an identity matrix. Taken together (see table 12), these two tests indicate that it is safe to proceed with and interpret the principle components analysis (Cascardi et al., 1999).

Table 17: Normality

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.898
Bartlett's Test of Sphericity	Approx: Chi-Square	14688.456
	df	703
	Sig.	.000

During analysis of the rotated components (loadings), poorly performing items (i.e., loadings well below the 0.60 standard) and items that correlated highly with unintended components (cross-loadings above 0.40) were removed one at a time as suggested by Hair et al. (1998). After each single item was removed, a new PCA was conducted and the above steps repeated. This allowed me to assess construct dimensionality in a very rigorous setting as the PCA algorithm artificially disallows correlations between items (Rook and Fisher, 1995). Therefore, I conclude the conditions for construct unidimensionality to be sufficiently met.

Next, I conducted second phase of testing the measurement model—using PLS—to assess factorial validity as suggested by Gefen and Straub (2005). This was done by conducting a confirmatory factor analysis (CFA) in which the pattern of loadings of the measurement items on the latent constructs was specified in the model. Results of the CFA showed that all measurement items loaded with significant t-values on the latent constructs (see table 18). This is an indication of convergent validity (Gefen and Straub, 2005).

Table 18: Confirmatory Factor Analysis

Item ←Construct	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	Standard Error (STERR)	T Statistics (|O/STERR|)
CU1 ← CTU	0.8679	0.8679	0.0159	0.0159	54.5952
CU2 ← CTU	0.9308	0.9307	0.0086	0.0086	107.7069
CU3 ← CTU	0.9347	0.9347	0.0079	0.0079	118.5413
CU4 ← CTU	0.8938	0.8938	0.0116	0.0116	76.8032
CU6 ← CTU	0.7626	0.7628	0.0313	0.0313	24.3744
Cmplx_2 ← Complexity	0.9317	0.9084	0.1028	0.1028	9.0678
Cmplx_3 ← Complexity	0.9386	0.9166	0.098	0.098	9.58
Cmplx_4 ← Complexity	0.9748	0.9582	0.0926	0.0926	10.5262
Crave1 ← Craving	0.897	0.8969	0.0126	0.0126	71.3319
Crave2 ← Craving	0.8885	0.8886	0.0111	0.0111	80.4031
Crave3 ← Craving	0.9253	0.9251	0.0092	0.0092	100.9888
Crave4 ← Craving	0.8708	0.8707	0.0144	0.0144	60.6269
Hab1 ← Habit	0.904	0.9039	0.0144	0.0144	62.9717
Hab1*PSC2 ← Habit * SunkCost	0.8474	0.8463	0.0286	0.0286	29.5957
Hab1*PSC3 ← Habit * SunkCost	0.8713	0.8699	0.0252	0.0252	34.6081
Hab1*PSC4 ← Habit * SunkCost	0.8609	0.8596	0.0274	0.0274	31.3774
Hab1*PSC5 ← Habit * SunkCost	0.8683	0.8679	0.0246	0.0246	35.2674
Hab1*PSC6 ← Habit * SunkCost	0.7662	0.7649	0.0481	0.0481	15.9201
Hab2 ← Habit	0.9166	0.9166	0.019	0.019	48.2377
Hab2*PSC2 ← Habit * SunkCost	0.8624	0.8583	0.0339	0.0339	25.4687
Hab2*PSC3 ← Habit * SunkCost	0.8776	0.8733	0.0332	0.0332	26.434
Hab2*PSC4 ← Habit * SunkCost	0.8474	0.8445	0.0417	0.0417	20.2999
Hab2*PSC5 ← Habit * SunkCost	0.8511	0.849	0.0404	0.0404	21.0644
Hab2*PSC6 ← Habit * SunkCost	0.7806	0.7769	0.052	0.052	14.9973
Hab3 ← Habit	0.9232	0.9227	0.0162	0.0162	56.8288

Table 18 continued

Item ←Construct	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	Standard Error (STERR)	T Statistics (|O/STERR|)
Hab3*PSC2 ← Habit * SunkCost	0.8596	0.8537	0.04	0.04	21.4967
Hab3*PSC3 ← Habit * SunkCost	0.9012	0.895	0.0349	0.0349	25.7901
Hab3*PSC4 ← Habit * SunkCost	0.8782	0.8714	0.0384	0.0384	22.8748
Hab3*PSC5 ← Habit * SunkCost	0.8921	0.8862	0.0351	0.0351	25.4404
Hab3*PSC6 ← Habit * SunkCost	0.7978	0.7907	0.0554	0.0554	14.405
Hab4 ← Habit	0.9402	0.9404	0.0079	0.0079	118.4269
Hab4*PSC2 ← Habit * SunkCost	0.8675	0.8653	0.0272	0.0272	31.8641
Hab4*PSC3 ← Habit * SunkCost	0.8903	0.8883	0.0254	0.0254	35.0634
Hab4*PSC4 ← Habit * SunkCost	0.8801	0.8774	0.0275	0.0275	32.0483
Hab4*PSC5 ← Habit * SunkCost	0.8841	0.8825	0.0247	0.0247	35.7526
Hab4*PSC6 ← Habit * SunkCost	0.808	0.8059	0.0423	0.0423	19.1007
Instab1 ← Instability	0.763	0.7263	0.1739	0.1739	4.3864
Instab3 ← Instability	0.852	0.8026	0.1544	0.1544	5.5165
Instab4 ← Instability	0.9067	0.8542	0.1491	0.1491	6.083
Instab5 ← Instability	0.941	0.8867	0.1647	0.1647	5.7136
PSC2 ← SunkCost	0.8424	0.8427	0.0158	0.0158	53.4259
PSC3 ← SunkCost	0.9175	0.9167	0.0106	0.0106	86.6969
PSC4 ← SunkCost	0.8987	0.8979	0.0123	0.0123	73.2212
PSC5 ← SunkCost	0.9104	0.9093	0.0126	0.0126	72.1744
PSC6 ← SunkCost	0.8199	0.8202	0.0217	0.0217	37.7625
Sat1 ← SatisControl	0.915	0.9149	0.0176	0.0176	51.8917
Sat2 ← SatisControl	0.9414	0.9412	0.0101	0.0101	92.8391
Sat3 ← SatisControl	0.9271	0.9271	0.0094	0.0094	98.2585
Sat4 ← SatisControl	0.8674	0.8669	0.0188	0.0188	46.1024
Triggers_4 ← Triggers	0.7978	0.7984	0.0335	0.0335	23.7917
Triggers_6 ← Triggers	0.8646	0.8639	0.0258	0.0258	33.541
Triggers_7 ← Triggers	0.7724	0.768	0.0448	0.0448	17.2373
Triggers_9 ← Triggers	0.882	0.8811	0.0211	0.0211	41.7068

To assess the discriminant validity of the measurement model I examined the correlations of the latent variable scores with the measurement items. This showed that all items loaded highly on their specified factor and not highly on other factors (see table 19). Loadings ranged from .76 (lowest) to .97 (highest).

Table 19: Cross-Loadings

	CTU	Complex	Craving	Habit	Instability	Satisfaction	Sunk Cost	Triggers
CU1	**0.87**	0.02	0.41	0.55	0.01	0.31	0.44	0.33
CU2	**0.93**	0.03	0.43	0.57	0.04	0.27	0.44	0.28
CU3	**0.93**	0.07	0.47	0.55	0.05	0.25	0.49	0.29
CU4	**0.89**	-0.03	0.48	0.57	-0.04	0.29	0.45	0.33
CU6	**0.76**	-0.02	0.44	0.46	-0.01	0.32	0.37	0.26
Cmplx_2	0.04	**0.93**	0.17	-0.05	0.44	-0.14	0.16	0.01
Cmplx_3	0.03	**0.94**	0.16	-0.07	0.44	-0.15	0.17	0.06
Cmplx_4	-0.01	**0.97**	0.14	-0.12	0.39	-0.12	0.12	0.02
Crave1	0.45	0.15	**0.90**	0.35	0.07	0.27	0.47	0.24
Crave2	0.48	0.05	**0.89**	0.42	0.00	0.32	0.44	0.28
Crave3	0.44	0.17	**0.93**	0.29	0.09	0.23	0.45	0.22
Crave4	0.44	0.20	**0.87**	0.32	0.09	0.23	0.48	0.21
Hab1	0.55	-0.08	0.37	**0.90**	-0.08	0.37	0.42	0.22
Hab2	0.58	-0.09	0.33	**0.92**	-0.07	0.32	0.36	0.27
Hab3	0.53	-0.11	0.35	**0.92**	-0.07	0.36	0.38	0.23
Hab4	0.60	-0.07	0.38	**0.94**	-0.07	0.39	0.43	0.30
Instab1	0.04	0.35	0.09	-0.04	**0.76**	-0.36	0.08	0.00
Instab3	0.02	0.38	0.05	-0.05	**0.85**	-0.33	0.04	0.01
Instab4	0.01	0.38	0.07	-0.06	**0.91**	-0.32	0.06	0.05
Instab5	0.00	0.41	0.05	-0.10	**0.94**	-0.39	0.02	0.04
PSC2	0.49	0.03	0.46	0.47	0.00	0.29	**0.84**	0.26
PSC3	0.42	0.20	0.41	0.33	0.08	0.27	**0.92**	0.22
PSC4	0.41	0.19	0.43	0.32	0.08	0.22	**0.90**	0.23
PSC5	0.39	0.19	0.42	0.32	0.08	0.28	**0.91**	0.21
PSC6	0.45	0.07	0.52	0.42	0.00	0.33	**0.82**	0.28
Sat1	0.34	-0.13	0.30	0.38	-0.35	**0.92**	0.31	0.18
Sat2	0.31	-0.13	0.27	0.36	-0.38	**0.94**	0.29	0.16
Sat3	0.27	-0.16	0.24	0.38	-0.41	**0.93**	0.28	0.19
Sat4	0.27	-0.09	0.26	0.30	-0.30	**0.87**	0.29	0.15
Triggers_4	0.30	0.10	0.24	0.25	0.03	0.13	0.24	**0.80**
Triggers_6	0.30	-0.04	0.23	0.25	0.01	0.19	0.24	**0.86**
Triggers_7	0.20	0.05	0.18	0.15	0.08	0.12	0.21	**0.77**
Triggers_9	0.29	0.00	0.21	0.24	0.01	0.17	0.22	**0.88**

To further assess discriminant validity I conducted an average variance extracted (AVE) analysis (see table 21). This test determines discriminant validity by examining whether the square root of the AVE for each latent construct is larger than any correlation among any pair of latent constructs (Fornell and Larcker, 1981). Results indicated that the AVEs were well above the.50 threshold and that the square roots of the AVEs were consistently larger than any other correlation (see tables 20 and 21). Results of this type provide evidence of discriminant validity (Chin, 1998).

Table 20: Correlations

	CTU	Complexity	Craving	Habit	Habit * Sunk Cost	Instability	Satisfaction	Sunk Cost	Triggers
CTU	1	0	0	0	0	0	0	0	0
Complexity	0.01	1	0	0	0	0	0	0	0
Craving	0.50	0.15	1	0	0	0	0	0	0
Habit	0.61	-0.09	0.38	1	0	0	0	0	0
Habit * Sunk Cost	-0.26	-0.03	-0.19	-0.33	1	0	0	0	0
Instability	0.01	0.43	0.06	-0.07	0.05	1	0	0	0
Satisfaction	0.32	-0.14	0.29	0.39	-0.25	-0.39	1	0	0
Sunk Cost	0.49	0.14	0.51	0.43	-0.13	0.05	0.31	1	0
Triggers	0.33	0.02	0.26	0.27	-0.12	0.03	0.18	0.27	1

Finally, I assessed the internal consistency reliability of the measurement model. This was done in PLS by calculating the composite reliability (CR) and Cronbach's Alpha (**α**) for each latent variable. Acceptable standards for composite reliability and Cronbach's Alpha are above the 0.70 threshold (Hair et al., 2011). Results showed that all composite reliability levels and Cronbach's alpha levels were well above the minimum threshold (see table 16).

Table 21: AVE, Reliability, R^2, α

	AVE	√AVE	CR	R^2	α
CTU	.77	.87	.94	.49	.92
Complexity	0.89	0.94	0.96	0	0.94
Craving	0.80	0.89	0.94	0	0.91
Habit	0.84	0.92	0.95	0.20	0.94
Habit * Sunk Cost	0.73	0.85	0.98	0	0.98
Instability	0.75	0.86	0.92	0	0.89
Satisfaction	0.83	0.91	0.95	0	0.93
SunkCost	0.77	0.87	0.94	0	0.92
Triggers	0.68	0.83	0.89	0	0.85

5.6 Testing the Structural Model

After concluding the measurement model was sound, I next assessed the structural model in SmartPLS (Ringle et al., 2005). The first step in assessing the structural model is done by calculating the R^2 values of the endogenous latent variables, and the path scores to determine the strength of the relationship. After examining the path scores, the second step in assessing the structural model is completed by the process of bootstrapping the model to determine path significance. According to Hair et al. (2011), the minimum number of bootstrap samples is 5,000, while the number of cases should be equivalent to the number of observations in the original sample. The third step in assessing the structural model is completed by determining the predictive relevance of the model by obtaining cross-validated redundancy measures for each construct. The final step in structural model assessment is completed through examining the heterogeneity of the model.

First, I examined all R^2 values (see table 16). Accepted standards for interpreting the endogenous latent variables in the structural model are the values of 0.75 (substantial), 0.50 (moderate), and 0.25(weak) respectively (Hair et al., 2011). Compulsive technology use had an

R^2 value of 0.49. Habit had an R^2 value of 0.20. Next, I examined all the individual path coefficients of the structural model. These values can be interpreted as standardized beta coefficients of OLS regressions. The path from habit to compulsive technology use had a score of 0.41. The path from perception of sunk cost to compulsive technology use had a score of 0.19. The path from the interaction variable habit*perception of sunk costs to compulsive technology use had a score of -0.05. The path from technology enabled triggers to habit had a score of 0.20. The path from complexity to habit had a score of -0.09. The path from instability to habit had a score of 0.10. The path from satisfaction to habit had a score of 0.38. The path from age to compulsive technology use had a score of -0.01. The path from craving to compulsive technology use had a score of 0.23.

After examining the R^2 values and standardized path coefficients, I followed the bootstrapping procedure as suggested by Hair et al., (2011) to determine the statistical significance of the paths (see table 17). I set my number of cases equal to my sample size and set the number of bootstrap samples equal to 5,000. This procedure enables the models estimated coefficients to be tested for their significance (Henseler et al., 2009). The results showed the critical t-values from the student's t-test (two-tailed) which can be interpreted as significant at the 0.10 level ($t = 1.65$), significant at the 0.05 level ($t = 1.96$), and significant at the 0.01level ($t = 2.58$). Using this critical t-value and the given degrees of freedom I also calculated p-values from the t distribution to aid in interpretation. The path from habit to compulsive technology use had a t statistic of 10.46 ($p < 0.01$). The path from perception of sunk costs to compulsive technology use had a t statistic of 5.19 ($p < 0.01$). The path from the interaction variable habit*perception of sunk costs to compulsive technology use had a t statistic of 1.42 ($p = 0.15$). The path from technology enabled triggers to habit had a t statistic of 6.12 ($p < 0.01$). The path from complexity to habit had a t statistic of 2.30 ($p = 0.02$). The path from instability to habit had a t statistic of 2.30 ($p = 0.02$). The path from satisfaction to habit had a t statistic of 7.76 ($p < 0.01$). The path from age to compulsive technology use had a t statistic of 0.45 ($p = 0.64$). The path from craving to compulsive technology use had a t statistic of 6.81 ($p < 0.01$).

Table 22: Total Effects

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	Standard Error (STERR)	T Statistic (|O/STERR|)	**P-value**
Complexity → CTU	-0.0393	-0.0388	0.0174	0.0174	2.2602	0.024306
Complexity → Habit	-0.0946	-0.0928	0.041	0.041	2.3056	0.021606
Craving → CTU	0.237	0.2358	0.0348	0.0348	6.8109	3.26E-11
Habit → CTU	0.4152	0.419	0.0397	0.0397	10.4641	5.43E-23
Habit * SunkCost → CTU	-0.0573	-0.0537	0.0402	0.0402	1.4245	0.155024
Instability → CTU	0.0454	0.0404	0.0203	0.0203	2.2438	0.025351
Instability → Habit	0.1095	0.0963	0.0475	0.0475	2.305	0.02164
Satisfaction → CTU	0.1593	0.1583	0.0285	0.0285	5.5909	4.01E-08
Satisfaction → Habit	0.3838	0.3766	0.0495	0.0495	7.7609	6.15E-14
SunkCost → CTU	0.19	0.1891	0.0365	0.0365	5.1988	3.1E-07
Triggers → CTU	0.0847	0.0882	0.0184	0.0184	4.6167	5.15E-06
Triggers → Habit	0.2041	0.2095	0.0333	0.0333	6.128	2.01E-09

The next assessment of the structural that is recommended involves analyzing the model's capability to predict (Hair et al., 2011). This was completed in PLS using blindfolding procedures using as recommended by Henseler, Ringle and Sinkovics (2009) to assess the model's prediction relevance via Stone-Geisser's Q^2 statistic (Geisser, 1975; Stone, 1974). Q^2 values above zero provide evidence that the model has predictive relevance; whereas values below zero indicate a lack of predictive relevance. Results of the blindfolding procedure to determine Q^2 (see table 23) for the endogenous variables showed values greater than zero (Q^2

CTU = 0.39, Q^2 Habit = 0.17). Similar to an effect-size evaluation, the relative impact of this measure can be interpreted as having predictive relevance that is small (0.02), medium (0.15), and large (0.35) (Henseler et al., 2009).

Table 23: Blindfolding for Q^2

Total	SSO	SSE	1-SSE/SSO
CTU	2215	1360.524	0.3858
Habit	1772	1464.395	0.1736

The final assessment of the structural model was then completed using finite mixture partial least squares segmentation (FIMIX-PLS). The FIMIX-PLS approach is able to ascertain the heterogeneity of the data structure on the assumption that heterogeneity is concentrated in the inner model relationships (Hair et al., 2011). This evaluation of the heterogeneity of observations is critical as unobserved heterogeneity can distort PLS results and threaten the validity of the research (Hair et al., 2011). Iterations of the FIMIX-PLS algorithm were done by sequentially increasing the number of subgroups (Sarstedt et al., 2011).

The fit indices AIC, BIC and CAIC were examined for each iteration to view which model would generate the lowest values, and thereby have the best fit. Additionally the fit index EN was examined to see which model had the highest EN value. The model with only two segments outperformed all other models as determined by lower values for AIC, BIC, CAIC, and a higher value for EN (see table 24). The segment sizes where then examined (see table 19). This analysis showed segment one contained 13.5 % of the total population and segment two contained 86.5% of the total population. Because the larger segment (segment 2) accounts for such a large percentage of the total population (86.5%) it can be concluded that any unobserved heterogeneity is not distorting the PLS results(Sarstedt et al., 2011).

Table 24: FIMIX-PLS

	2 Segments	3 Segments	4 Segments	5 Segments
AIC	2245.32	2516.67	2435.33	2439.89
BIC	2364.04	2696.78	2676.85	2742.82
CAIC	2364.10	2696.88	2676.98	2742.98
EN	0.65	0.45	0.60	0.59

5.7 Hypothesis Testing

Having concluded that the measurement model and structural model meet the necessary standards to test the model hypotheses, I next examined each hypothesis in turn. I used PLS-SEM to gauge the magnitude, direction and significance of each hypothesized effect. In addition to t statistics, I also calculated p-values for ease of interpretation.

Hypothesis 1

Hypothesis 1 states that technology habit will be positively associated with compulsive technology use. As seen in figure 3, this hypothesis is supported. The path from technology habit to compulsive technology use had a standardized path coefficient of 0.41. Results from the bootstrapping procedure provided a statistically significant t statistic of 10.46. Given the sample size and degrees of freedom, I computed a p-value to aid in interpretation of the t statistic. The p-value is <0.001.

Hypothesis 2

Hypothesis 2 stated that perception of sunk costs will moderate the effect of technology habit on compulsive technology use such that as perception of sunk costs increases the positive relationship between technology habit and compulsive technology use becomes stronger. The testing of this hypothesis first requires testing the direct path from perception of sunk costs to compulsive technology use. This path was significant with a standardized path coefficient of 0.19. Results from the bootstrapping procedure provided a statistically significant t statistic of 5.19. Given the sample size and degrees of freedom, I computed a p-value to aid in interpretation of the t statistic. The p-value is <0.001. Next, a standardized interaction term was created to test the direction and strength of the moderation hypothesis. As seen in figure 3, this effect was not significant. The moderation variable had a standardized path coefficient of -0.05. Results from the bootstrapping procedure provided a statistically insignificant t statistic of 1.42. Given the sample size and degrees of freedom, I computed a p-value to aid in interpretation of the t statistic. The p-value is = 0.15. Therefore hypothesis 2 is not supported.

Hypothesis 3

Hypothesis 3 stated that technology instability will be negatively associated with technology habit. Results showed that the path from technology instability to technology habit had a standardized path coefficient of 0.10. Results from the bootstrapping procedure provided a statistically insignificant t statistic of 2.30. Given the sample size and degrees of freedom, I computed a p-value to aid in interpretation of the t statistic. The p-value is = 0.02. Though an effect was detected and the effect was statistically significant, I had hypothesized a negative effect instead of a positive effect. Therefore hypothesis 3 is not supported.

Hypothesis 4

Hypothesis 4 stated that technology complexity will be negatively associated with technology habit. Results showed that the path from technology complexity to technology habit had a standardized path coefficient of -0.09. Results from the bootstrapping procedure provided a statistically significant t statistic of 2.30. Given the sample size and degrees of freedom, I computed a p-value to aid in interpretation of the t statistic. The p-value is = 0.02. Therefore, as reflected in figure 3, hypothesis 4 is supported.

Hypothesis 5

Hypothesis 5 stated that technology-enabled triggers will be positively associated with technology habit. Results showed that the path from technology-enabled triggers to technology habit had a standardized path coefficient of 0.08. Results from the bootstrapping procedure provided a statistically significant t statistic of 4.61. Given the sample size and degrees of freedom, I computed a p-value to aid in interpretation of the t statistic. The p-value is <0.001. Therefore, as reflected in figure 3, hypothesis 5 is supported.

Hypothesis Summary

Table 25 shows the findings of the hypothesized effects according to the direction and significance of the tested paths. Results showed that:

- H1, H4, and H5 are all fully supported as hypothesized.
- H2 and H3 were not supported.
- H2 was not significant and the effect was found to be opposite of the hypothesized direction.
- H3 was significant, however the direction of the path was opposite of the hypothesized direction.

Table 25: Hypotheses Results

	Research Model Hypotheses	Results
H1	Technology habit will be positively associated with compulsive technology use	Supported
H2	Perception of sunk costs will moderate the effect of technology habit on compulsive technology use such that as perception of sunk costs increases the positive relationship between technology habit and compulsive technology use becomes stronger	Not supported. The direct effect was positive and significant as predicted. However, the moderation was weak and negative and only significant at approximately the .15 level.
H3	Technology instability will be negatively associated with technology habit	Not supported. The relationship was significant; however, it was positive instead of negative.
H4	Technology complexity will be negatively associated with technology habit	Supported
H5	Technology-enabled triggers will be positively associated with technology habit	Supported

Figure 3 shows the results of the structural model. All paths are significant at or below the 0.05 level with the exception of the interaction (moderation) effect. This moderation effect was only significant at the 0.15 level. However, the direct effect from perception of sunk costs to compulsive technology use (not shown) had a path coefficient of 0.19 and was highly significant with a t statistic of 5.19 ($p < 0.001$). Of peculiar interest was the finding that two of the hypothesized effects (H2 and H3) were found to operate in the opposite direction. These unexpected results are further discussed in the next chapter.

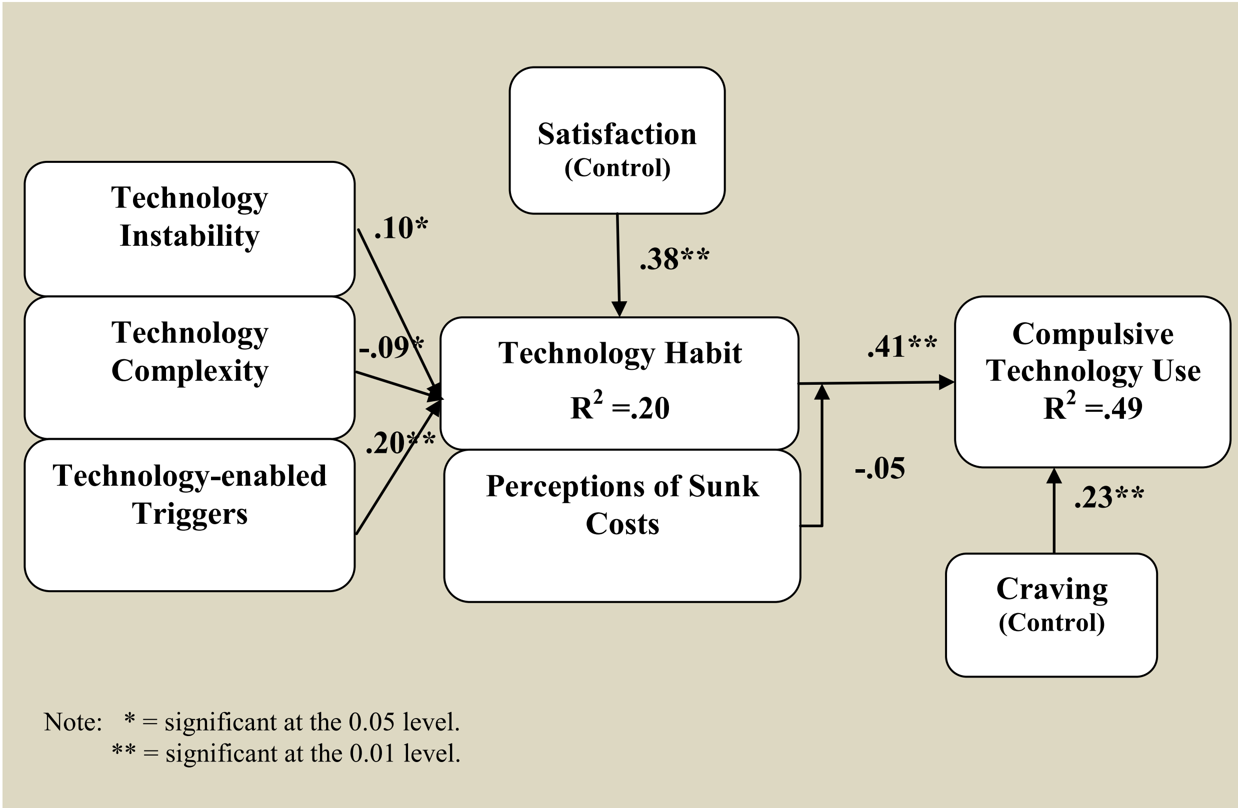

Figure 3: PLS Results

5.8 Summary

In summary, this chapter presented the results of the data analysis. The testing of the structural model was presented followed by a presentation of the testing of the structural model. The testing of the hypotheses was also presented. In the next chapter, I will discuss these findings as well as discuss some of the limitations of the study.

CHAPTER 6

DISCUSSION, LIMITATIONS, CONTRIBUTIONS

6.1 Introduction

In this chapter, I will briefly review the purpose of this dissertation. Next, I will provide a discussion of the hypotheses and findings. I will then address some of the contributions as well as limitations of this research. I will conclude with a discussion of possible directions for future research.

6.2 Review of Purpose

One way that an organization can determine whether a technology implementation is successful is to determine how much the technology is being used by individuals (Mason and Mitroff, 1973). MIS research has a long tradition of using individual engagement as a proxy for system success (DeLone and McLean, 1992). This tradition of research has demonstrated that technology has the capability to engage users in a variety of ways (Kim and Malhotra, 2005). The bulk of this research stream has focused on the intentional use of information technologies. These technologies can primarily be classified as mandatory-use technologies that have been implemented by an organization.

The bulk of traditional research related to technology usage behaviors can be classified as being part of the core MIS dimension: information system use. This research stream has examined the acceptance (Davis et al., 1989), adoption (Moore and Benbasat, 1991), and continued use (Bhattacherjee, 2001) of technologies. Research in this area has primarily focused on an individual's behavioral intention to use a mandatory information system in the context of their occupation (Bhattacherjee et al., 2008; Davis et al., 1989; Venkatesh and Davis, 1996;

Venkatesh et al., 2003). Research in this stream has been based on theories of intentional behavior. Two dominant theories have been the theory of reasoned action (Ajzen and Fishbein, 1975), and the theory of planned behavior (Ajzen, 1991). Both theories are grounded in the core belief that behavior is predominately planned and intentionally performed. Therefore, MIS research based on these theories has focused on technology usage behaviors that are planned and intentional.

More recently, research has demonstrated that certain behaviors are neither planned nor intentional (Kim, 2009; Kim and Malhotra, 2005; Kim et al., 2005). This recent research has suggested that MIS researchers need to develop new theories for behaviors that are unplanned and unintentional (de Guinea and Markus, 2009). Research in this stream has looked at how behavioral intention—which was once so dominant in MIS research—can be inhibited by stronger psychological mechanisms (Limayem et al., 2007). Psychological mechanisms such as sunk costs (Polites and Karahanna, 2012), habits (Venkatesh et al., 2012a), automatic behaviors (Kim et al., 2005) and addictions (Turel et al., 2011a) have been shown to drive technology use behaviors directly. However, this research is still in its infancy as researchers have yet to identify how these unplanned, automatic and uncontrollable behaviors come to be.

In today's world, information technology is everywhere and it engages users in a many different ways. No longer constrained to traditional information systems in organizational contexts, technology has become much more pervasive and personalized. As individuals are increasingly exposed to the types of triggers that prompt automatic technology engagement, technology use has evolved and moved beyond the bounds of intentionality. There are numerous popular press and news stories which point to technology-use behaviors that may become automatic or difficult to control. Individuals can begin to develop spontaneous-use behaviors and feel compelled to interact with the technologies they use. This dissertation addresses this new type of technology use, and names it compulsive technology use. The primary goal of this dissertation is to begin to address the gap in our understanding of what is triggering this non-intentional and compulsory technology engagement behavior. The research question guiding this dissertation is, "How do the characteristics of a technology influence compulsive technology use?"

To provide a theoretical foundation for the dissertation and lens to begin to address the research question, I adapted a general theory of automatic behavior as described by Simon (1947). This theory postulates that there are two principle sets of mechanisms which contribute to automatically performed behaviors. The first set is the initiatory mechanisms which are external to the individual and serve to cue and trigger behavior into motion. Adapted to the dissertation, these external mechanisms can be viewed as elements of technology design such as the relative instability, complexity and various technology-enabled triggers. The second set of mechanisms is the persistence mechanisms which are internal to the individual (psychological) and which contribute to and compel behaviors to persist. Adapted to the dissertation, these internal mechanisms are identified as technology habit and perception of sunk costs. Adapting Simon's (1947) theoretical framing to the context of this dissertation allows for the exploration of the research question and the identified phenomenon compulsive technology use.

6.3 Summary of Hypotheses and Findings

The general purpose of this dissertation has been the exploration of question of what drives compulsive technology use. To begin to understand this phenomenon, the specific research question that has guided this study has been "How do the characteristics of a technology influence compulsive technology use?" There are some key assumptions to this research question which should be noted. First, compulsive technology use is not solely a behavior performed in isolation. Compulsive technology use is an interaction of someone with something tangible and external. That something tangible and external is a technology, therefore there must be some characteristics of the technology which contribute to the behavior. The specified technology used to address the research question of this dissertation was mobile applications. As such, certain important characteristics of mobile applications—such as key elements of technology design—must be identified. Second, compulsive technology use is a behavior of a person. When people do things, psychological processes must first be activated which signal to the person how to "do" (Bandura, 1977). Because compulsive technology use is a behavior, there must be something internal (psychological) to the individual that can begin to address the "how" of this dissertation. In essence, the research question is addressing how some external thing can cause a person to behave in a certain way. Stated differently, "How (by which psychological processes cause) do the characteristics of a technology (elements of technology design) influence compulsive technology use (a person interacting with technology in a certain way)? To address this research question, a review of the relevant research was conducted. From this review, a research model and specific hypotheses were developed to address the research question and to understand the phenomenon of compulsive technology use.

The research model captured important characteristics of technology that contribute to the phenomenon of compulsive technology use. These important characteristics are elements of technology design that fit within the proposed theoretical framing of being external to the individual. These elements of technology design serve to guide an individual's engagement with technology. They are identified as technology instability, technology complexity, and technology-enabled triggers.

To address the “how” of the research question, I relied on the theoretical framing from Simon (1947). Key mechanisms of behavioral persistence were identified. These mechanisms are psychological mechanisms that cause technology usage behaviors to persist once those behaviors have been engaged. This dissertation identified technology habit and perception of sunk costs as two important psychological persistence mechanisms which address the “how”.

The first hypothesis stated that technology habit would be positively associated with compulsive technology use. This hypothesis addressed the “how” of the research question. Technology habit is a psychological persistence mechanism which was hypothesized to contribute to compulsive technology use. The results from the statistical analyses performed supported this claim. The stronger an individual’s technology habit, the more compulsive the behavior.

The second hypothesis also addressed the “how” of the research question. The second hypothesis stated that perception of sunk costs would moderate the effect of technology habit on compulsive technology use. This indicated that as perception of sunk costs increased, the positive relationship between technology habit and compulsive technology use would become stronger. In effect, technology habit and perception of sunk costs were thought to interact and strengthen the relationship between technology habit and compulsive technology use. The results from the statistical analyses performed were not entirely supportive of this claim. The findings showed that perception of sunk costs directly contributed to compulsive technology use. High levels of perception of sunk costs were associated with high levels of compulsive technology use. However, perception of sunk costs did not strengthen technology habit’s effect on compulsive technology use. This unexpected finding is further discussed in section 6.3.

The third, fourth, and fifth hypothesis addressed the “characteristics of technology” portion of the research question. The third hypothesis stated that technology instability would be negatively associated with technology habit. This would indicate that high levels of technology instability would be associated with low levels of technology habit. The results from the statistical analyses performed were not supportive of this claim. Though a statistically significant effect was observed, it was a positive effect instead of a negative effect. This counter-theoretical and unexpected finding is further discussed in section 6.4.

The fourth hypothesis stated that technology complexity would be negatively associated with technology habit. The more complex a technology is the less likely a person is to have developed strong habits. Thus, high levels of technology complexity should be associated with low levels of technology habit. The results from the statistical analyses performed supported this claim.

The fifth hypothesis stated that technology-enabled triggers would be positively associated with technology habit. The more cues and triggers designed into technology the higher the level of technology habit. The results from the statistical analyses performed supported this claim. Individuals that rated technology-enabled triggers high also saw higher levels of technology habit. Thus, technology-enabled triggers are positively associated with technology habit.

Taken together, the hypotheses addressed the stated research question of how technology features influence compulsive technology use. In the next section, I will discuss some of these findings in more detail. Specifically, I will address the unexpected results from the test of the hypotheses.

Table 26: Review of Hypotheses

	Research Model Hypotheses	Results
H1	Technology habit will be positively associated with compulsive technology use	Supported
H2	Perception of sunk costs will moderate the effect of technology habit on compulsive technology use such that as perception of sunk costs increases the positive relationship between technology habit and compulsive technology use becomes stronger	Not supported. The direct effect was positive and significant as predicted. However, the moderation was weak and negative and only significant at approximately the 0.15 level.
H3	Technology instability will be negatively associated with technology habit	Not supported. The relationship was significant; however, it was positive instead of negative.
H4	Technology complexity will be negatively associated with technology habit	Supported
H5	Technology-enabled triggers will be positively associated with technology habit	Supported

6.4 Discussion of Unexpected Findings

There were two unexpected findings from the test of the hypotheses. H2 and H3 could not be fully supported due in part to the direction of the hypothesized path. I will address these findings in turn. First, I will discuss the peculiar finding from the moderation effect (not significant and negative rather than positive), and then I will discuss the peculiar finding from the positive (rather than negative) path from technology instability to habit.

The ability to detect and accurately estimate interaction effects which help explain the conditions and contexts in which the relationships between variables may vary is critical in IS research (Chin et al., 1996). In order to test for a moderation effect you must first test the direct effect. Though this path is not specifically hypothesized in the model it is understood that this path should be significant (Baron and Kenny, 1986). Then an interaction variable must be created and tested in the model. Traditionally this was done using either an analysis of variance (ANOVA) or a moderated multiple regression (MMR); however, both techniques have been shown inferior to PLS approaches (Chin et al., 2003). After the interaction effect is modeled, the strength and direction of the effect can be determined.

I had originally hypothesized that I would find a positive effect. This means that I expected that an increase in an individual's perception of sunk costs would strengthen habit's effect on compulsive technology use. Meaning, the higher the sunk costs, the more habit would influence compulsive technology use. However, the results (though they are not statistically significant and must be carefully interpreted) showed exactly the opposite. Heightened perception of sunk costs actually decreased the effect of habit on compulsive technology use.

This unexpected finding is perplexing as the direct effects from both variables that are used to create the interaction variable were strong and positively related to compulsive technology use. The direct effect from habit to compulsive technology use was positive and significant. The direct effect from perception of sunk costs to compulsive technology use was positive and significant. However, the interaction effect (i.e., the effect from habit * perception of sunk costs to compulsive technology use) was negative and not significant. This effect demonstrates that there may be other unseen variables at play (Hayes, 2009) affecting how perception of sunk costs influences compulsive technology use.

To investigate this possibility, I engaged in a post-hoc analysis using PLS. Results of the post-hoc analysis showed that age played a significant role and affected the perception of sunk costs to compulsive technology use relationship. This finding showed that the older an individual was the more that perception of sunk costs influenced their compulsive technology use; whereas the younger the individual, the less the influence (path coefficient = .07, t value = 2.61). Further analysis investigating the effect of age on perception of sunk costs showed that age negatively and significantly influenced perception of sunk costs (path coefficient = -0.12, t value = 3.61). This could be an indication that young people interacting with a technology are not as affected by their perception of sunk cost as are older people interacting with a technology. Because the median age for the sample population was quite young, this finding though not externally generalizable may provide an explanation for the unexpected direction (though not statistically signification) of the moderation effect. More research is warranted to further explore the relationship between technology habit, perception of sunk costs, and compulsive technology use.

The second unexpected finding from the testing of the hypotheses was from H3 which hypothesized that technology instability would be negatively associated with technology habit. Theoretically, the more instable a technology is, the less likely a person is to develop strong technology habits. This is due to the fact that habits need a stable context in which they (the habits) can be repeatedly performed. This logic led to the hypothesis that in the context of technology use, a very unstable technology (technology instability) should correspond with lower levels of technology habit. The results showed that this was not the case; in fact just the opposite was true. High levels of technology instability were positively associated with technology habit.

To begin to investigate this perplexing finding, I first analyzed the item to item correlations. Viewing the correlations in isolation, it appears that technology instability items are negatively correlated with items that they should theoretically be negatively correlated with, such as satisfaction items and technology habit items. It also appears that the technology instability items are positively correlated with items that they should theoretically be correlated with such as technology complexity. This led me to two different scenarios which may possibly account for the unexpected result. The first scenario I investigated was that the results may be affected by the existence of multicolinearity. The second scenario I investigated was that I may have failed to appropriately specify the model.

To investigate whether multicolinearity was affecting the model, I examined the correlations for technology instability and technology complexity. Theoretically, these two constructs should correlate to some extent as they are related concepts. However, they should not be overly correlated (Kenny, 1979). The results demonstrated that both the item to item correlations and the construct correlations were not overly strong. Correlations for the items were 0.35, 0.38, 0.38, and 0.41. The construct correlation was 0.43. These are well below the suggested bivariate correlation heuristics of 0.85 (Kline, 2004) or 0.90 (Hayduk, 1988) which are used to suggest issues multicolinearity. Next, I examined the standard errors from the original model and the bootstrapped model. Results from the bootstrapping analysis showed that there was not a large increase in the standard errors from the original model to the bootstrapping model. Taken together this suggests that multicollinearity is not affecting the model (Kline, 2011).

Next, I investigated whether I incorrectly specified the model. My suspicion was that I had failed to include an important mediator between technology instability and technology habit. As suggested by Baron and Kenny (1986) and others (Zhao et al., 2010) an unexpected sign change may result from an omitted mediator. Given the fact that technology instability and satisfaction should theoretically be inversely correlated, I further examined this relationship. Following the mediation testing approach of Zhao, Lynch and Chen (2010), I looked at satisfaction as a "competitive mediator" for technology instability and technology habit. Competitive mediation occurs when the sign of the effect from X→M is opposite the sign of the effect from M→Y. In this instance, technology instability is negatively correlated with satisfaction; satisfaction is positively correlated with technology habit. The resulting direct effect from X→Y would demonstrate a sign change (i.e., instead of a negative effect as I hypothesized, I saw a positive effect).

First, I analyzed the direct effects of the paths in isolation with bootstrapping to determine significance. Results from this post hoc analysis showed that the path from technology instability to satisfaction had a path coefficient of -0.40 (R^2 of satisfaction = 0.16) with a t score of 9.37. The path from satisfaction to technology habit had a path coefficient of 0.37 with a t score of 8.04. The path from technology instability to technology habit had a path coefficient of 0.11 with a t score of 2.45. Next, I ran the mediated model with all the paths added back in and examined the bootstrap results to see whether the direct path from technology instability remained significant. The results showed that the direct effect was now in the correctly hypothesized direction (i.e., it was negative as I had originally hypothesized) with a path coefficient of -.04, but it was no longer significant with a t score of 0.79. Following the guidelines of Zhou et al., (2010) this is a demonstration of competitive mediation.

This finding helps explain the unexpected sign change observed when testing H3. It is likely that this occurred by omitting the important competitive mediator satisfaction in the relationship between technology instability and technology habit. As a result of this omission, the observed direct effect was counter-theoretical to the hypothesized effect. Further research in this area is warranted as this post-hoc analysis does not fully explore (nor explain) the relationship between these variables.

6.5 Implications for Theory

Understanding the phenomenon of compulsive technology use has several theoretical implications. From a research standpoint, this fills a gap in the call for research with a design science orientation (Hevner et al., 2004) as elements of technology design can drive behaviors. Understanding the technology features which enable high levels of compelling interaction will allow for the study of and design of high use voluntary type technologies. Current IS usage models and theories have had difficulty explaining technology use in this voluntary use paradigm. This dissertation reflects "an important assumption that seems to be missing in the IS literature on continuing IT use, namely, that IT itself may be one of the most important triggers of automatic IT use behaviors" (de Guinea and Markus, 2009). This dissertation explored elements of technology design and developed the concept of technology-enabled triggers that prime technology usage behaviors. Incorporating aspects of technology design into current theorizing places emphasis on the IT artifact and helps distinguish MIS scholarship. Techno-centric theorizing can help researchers to make more informed decisions on how the design of technology can impact future technology use.

Another contribution stems from the development of the concept of compulsive technology use as a new IS dependent variable. There has been a growing interest in IS research to understand an individual's continued use well after initial adoption. Paired with this is the notion that much technology use occurs outside of an organization's mandate to use a particular technology. A large portion of post-adoption technology use can be classified as personal use that is voluntary in nature. Research has yet to fully address how individuals engage with technology in this new context. Developing the concept of compulsive technology use provides insight into a technology engagement behavior that can occur in this context, which has yet to be fully explored. Future research can further develop and explore this phenomenon in a variety of settings—whether they are personal contexts (e.g., mobile gaming) or organizational contexts (e.g., an organization's "bring your own device" policy). Using compulsive technology use as a dependent variable rather than intentional technology use may better explain an individual's continued use of voluntary technologies well after initial adoption.

Another contribution of this research is the more fully developed and conceptualized construct perception of sunk costs as a predictive measure of future behavior. Classic sunk cost research has relied extensively on actual monetary sunk costs to determine the likelihood of future behavior. However, monetary sunk costs are only one part of a tripartite concept. This dissertation presents a more fully developed tripartite concept of perception of sunk costs which includes money, time and effort. This development should be particularly beneficial to research on free, trial-based, or open-sourced technologies. As currently developed by this dissertation, the concept of perception of sunk cost can now be applied to explore how individuals and organizations interact with technologies in contexts where little or no money was actual spent.

Finally, the development and exploration of the phenomenon of compulsive technology furthers our understanding of technology behaviors that are not motivated by classical theories of behavioral intent. It is possible that foundational pieces of IS research based on intentionally driven theories such as TRA or TPB should be revisited as they likely fall short of explaining how people actually interact with technologies. Much technology use cannot be confined within the basic premise that technology use is fundamentally intentional behavior. This answers the call for MIS research that uses behavioral frameworks which are more affect based, less rational, and more unintentional (de Guinea and Markus, 2009) to understand how individuals interact with technology. Much of human behavior can be classified as automatic (Aarts et al., 1998) and understanding compulsive technology use can provide insight into understanding other automatic technology engagement behaviors.

6.6 Implications for Practice

This research also provides several implications for business practitioners. One contribution stems from the notion that mobile applications can be purposefully designed with certain features that can either enable or inhibit compulsive interaction with the system. This will allow more efficient systems to be designed with the necessary features to promote the type of technology engagement desired. For example, if extremely high compulsive engagement is desired (e.g., casino type gaming applications), then certain functionalities which are pre-programmed into a mobile app platform (vibrations, tones, lights) can be "switched-on" and incorporated by those developing on the platform. By increasing the amount of and the visibility of the technology-enabled triggers used by an application, developers can likely raise baseline levels of compulsive engagement by the end-users. However, if the desired functionality is more utilitarian (e.g., financial banking applications) and developers wish to inhibit compulsive interactions, then those certain functionalities which engage compulsive behaviors can be "switched-off" and not used by those developing on the platform.

Another contribution stems from the development of the concept of perception of sunk costs. Heightened perceptions of sunk costs are shown to be associated with compulsive technology use. It may be difficult for a developer to directly influence an individual's compulsive technology use. However, increasing an individual's attention to the costs associated with his or her use of the technology will complement and strengthen his or her compulsive technology use. By highlighting just how much has gone into the use of a particular technology—in terms of the monetary investments, time investments and effort investments—developers can expect an increase in compulsive technology use. From a design standpoint, features which convey this type of information to the user can be included to increase the amount of perception of sunk costs. The more the end-user is aware of just how much time and effort they have invested using a mobile application, the more they will feel compelled to use it in the future.

6.7 Limitations

This dissertation has some limitations which must be acknowledged. They can be classified into one of the three following categories: 1) the cross-sectional survey design, 2) the convenience sample, 3) the target mobile application. These limitations have the potential to reduce the study's external generalizability. I will discuss each of these briefly.

The first limitation to this dissertation is the chosen research design method. Cross-sectional research designs collect data at one point in time from a sample of individual's that represent the population of interest. Inferences are made from the sample and then generalized to the population of interest. However, this limits the ability to inference causality because the "study is conducted at one point in time and temporal priority is difficult to establish" (Pinsonneault and Kraemer, 1993). A longitudinal approach which measures the amount of compulsive technology use over time could provide additional insight into the process of how compulsive technology use behaviors develop over time. However, this was not the aim of this dissertation. This dissertation looked at how different factors of technology design influence compulsive technology use. As such, it is not attempting to establish or determine causality of the phenomenon, and relies on the causality suggested by the theoretical framing.

The second limitation to this dissertation is the convenience sample of college students used. At the onset of the research college students were thought to be a sufficient source for sampling because they represent a diverse population of individuals who are experienced using mobile applications. However, one aspect of this sample demographic proved to be an unlikely factor which emerged as a possible source of a confounding effect on perception of sunk costs. This was the age range of the sample. The post-hoc analysis performed suggests that younger individuals are not as susceptible as older individuals to the effects of perception of sunk costs that were hypothesized to influence the habit to compulsive technology use relationship. Due to the relatively restricted age range, this interesting finding has limited generalizability outside of this current study. However, this limitation has potential research implications as age may prove to be an important mediator of other technology-use type behaviors.

A third limitation to this dissertation is the restricted target mobile applications that were used for the study. Individuals were limited to choosing only Twitter or Facebook to respond to the survey questions. They were not allowed to choose whatever mobile app or technology that they felt they used the most compulsively. Because both of the target applications used for data collection are social media applications, it is possible that this may limit the generalizability of the findings on compulsive technology use into other technologies (non-social media applications). However, since the results showed no significant group effects between Twitter users and Facebook users on the variables in the study it is likely safe to generalize the results to other social media applications. The implications for research and practice should prove particularly appropriate for future studies on a variety of social media platforms.

6.8 Future Research

This dissertation had a very specific scope in the exploration of the phenomenon of compulsive technology use. This presents an opportunity for future research to further explore and expand onto this work. Several directions for future research have been identified which will be discussed in turn.

First, future work should examine the causal nature of the phenomenon. Compulsive technology use represents a stage of technology use which has become automatic and compulsory. It represents a stage of technology use that has gone well beyond initial adoption decisions and subsequent continuance decisions. This dissertation identified several variables which contribute to this phenomenon. However, the process by which this compulsory behavior develops was not in the scope of the current study. This provides an opportunity for future research that examines this process over time. Likely a longitudinal study of individuals which captures technology behaviors at several points in time (over a long period of time) is warranted to understand the causal nature of the phenomenon. Information should be collected before interaction with a new technology, during interaction with the technology and long into continued interaction with the technology.

Second, future work should examine characteristics of individuals that compulsively use technology. This dissertation only addressed how technology characteristics influence compulsive technology use. There are likely other characteristics that are not related to the technology itself which may contribute to compulsive technology use. This provides an opportunity for future research which addresses other factors which may contribute to compulsive technology use. One suggested factor that may prove fruitful is personality. It is likely that different people are more affected by elements of technology design than others. For example, people with highly impulsive personalities might be more affected by the way technology triggers behavior than people with more conscientious personalities. Future research should identify those individual characteristics which may contribute to or inhibit compulsive technology use.

Third, future work should examine the phenomenon of compulsive technology use with other technologies. This dissertation focused on mobile social media applications. Furthermore, the type of application-use was targeted to personal and non-work related use. It is possible that individual's compulsively interact with technologies as part of their jobs. This provides an opportunity for future research looking at compulsive technology use within an organization. This is a promising avenue for researchers looking into IT consumerization and BYOD (bring your own device) initiatives. Compulsive technology use may have organizational consequences that have yet to be identified. Researchers exploring the impact of personal technology use as part of an organizational objective should examine the effects of compulsive technology use on the organization.

Finally, future work should begin to address the consequences of compulsive technology use. This dissertation provided no judgment on whether compulsive technology use is a good thing or a bad thing. From a developer standpoint it is possibly a very good thing that could mean highly successful mobile applications that see high levels of consumer use. From an organization standpoint it is possible compulsive technology use means more productive employees who effortlessly engage with technology to complete their tasks. However, from a psychological standpoint it is possibly a very bad thing to the detriment of the user with numerous—personal, social and work-related—negative consequences. These possible outcomes of compulsive technology use have yet to be identified. This provides an opportunity for future research to explore the variety of possible positive and negative consequences in different contexts.

6.9 Summary

Understanding the different ways individuals interact with technology has been an important aspect of MIS research since its inception. The pervasive and often invasive presence of technology in business and society today has changed the way businesses and people do things. Human behavior is not always consciously and intentionally driven. Technology use behaviors can be driven automatically, non-rationally, and unintentionally. This phenomenon is referred to as compulsive technology use. Technology itself may be one of the most dominant triggers of this compulsive human-technology interaction.

This dissertation explored the phenomenon of compulsive technology use. This exploration was guided by the research question of "How do the characteristics of a technology influence compulsive technology use?" A theoretical framework of automatic behaviors was utilized to identify key technological mechanisms of behavioral initiation and psychological mechanisms of behavioral persistence which contribute to compulsive technology use. The mechanisms of behavioral initiation are elements of technology design and were identified as: technology instability, technology complexity and technology-enabled triggers. The mechanisms of behavioral persistence are psychological in nature and were identified as: technology habit and perception of sunk cost.

The application of the theoretical framing allowed for the development of specific hypotheses to address the stated research question. These hypotheses were constructed into a research model of compulsive technology use. Measures were then developed to capture and quantify the research models theoretical constructs. This research methodology used a survey research design to sample individuals that are part of population of compulsive technology users. Statistical analyses were then performed on the responses from this sample to address the hypothesized research model. The results of the analyses allows for making inferences about the findings to the population of compulsive technology users.

The results of the hypothesis testing were then addressed in turn. Findings were generally consistent with the proposed research model. Results showed that the characteristics of technology (as previously identified) contributed to the proposed psychological mechanism of persistence. The psychological mechanisms of persistence (as previously identified) contributed to compulsive technology use. Any deviations for the proposed research model were addressed in turn.

The findings of this dissertation have both theoretical and practical implications. These implications were each addressed in turn. From a research standpoint, techno-centric theorizing can aid researchers make more informed decisions on how the design of technology can impact future technology use. Additionally, using compulsive technology use as a dependent variable rather may better explain an individual's continued use of voluntary technologies well after initial adoption. As currently developed by this dissertation, the concept of perception of sunk cost can now be applied to explore how individuals and organizations interact with technologies in contexts where little or no money was actual spent. Finally, the development and exploration of the phenomenon of compulsive technology furthers the understanding of technology behaviors that are not motivated by behavioral intent.

From a practitioner standpoint, this dissertation suggests that mobile applications can be purposefully designed with certain features that can either enable or inhibit compulsive interaction with the system. Developers can utilize this knowledge to design more efficient technologies with the necessary features to promote the type of technology engagement desired. Additionally, increasing an individual's attention to the costs associated with his or her use of the technology will complement and strengthen his or her compulsive technology use. From a design standpoint, features that convey this type of information to the user can be included to increase the amount of perception of sunk costs. By highlighting just how much has gone into the use of a particular technology—in terms of the monetary investments, time investments and effort investments—developers can expect an increase in compulsive technology use.

This dissertation had some limitations which were acknowledged. These limitations were addressed as they have the potential to reduce the external generalizability of the findings. The limitations identified and discussed included the research design method, the sample population and the chosen social media applications as a proxy for technology. After the limitations were addressed several directions for future work were identified.

This dissertation only begins to answer a small question concerning the phenomenon of compulsive technology use. There are several areas of interest that future research needs to address. First, future work should examine the causal nature of the phenomenon. Second, future work should examine characteristics of individuals that compulsively use technology. Third, future work should examine the phenomenon of compulsive technology use with other technologies and in other contexts. Finally, future work should begin to address the unknown consequences and outcomes of compulsive technology use.

APPENDIX A

SURVEY INSTRUMENT

Instructions: The following statements refer to your personal and voluntary use of Facebook, Twitter, or Instagram. If you use these apps as part of your job, please think of your personal use instead of your work-related use as you read the statements. As you read the following statements, think about the mobile app that you use most frequently as you circle your response

Which mobile app do you use most frequently? [ ] Facebook [ ] Twitter
How long have you been using this mobile app? [ ] A few weeks [ ] A few months [ ] Under 1 year [ ] Over 1 year [ ] Well over 1 year

As you read the following statements, think about the mobile app you use the most frequently as you circle your response

Technology Instability	**Strongly Disagree**	**Disagree**	**Somewhat Disagree**	**Neutral**	**Somewhat Agree**	**Agree**	**Strongly Agree**
This technology is unstable	1	2	3	4	5	6	7
This technology has to update frequently	1	2	3	4	5	6	7
I often cannot get this technology to work properly	1	2	3	4	5	6	7
This technology behaves in unpredictable ways	1	2	3	4	5	6	7
This technology tends to be unreliable	1	2	3	4	5	6	7

How do you feel about your overall experience using this mobile app?						
Very Dissatisfied 1	2	3	4	5	6	**Very Satisfied** 7
Very Displeased 1	2	3	4	5	6	**Very Pleased** 7
Very Frustrated **1**	2	3	4	5	6	**Very Contented** 7
Absolutely Terrible 1	2	3	4	5	6	**Absolutely Delighted** 7

Technology-enabled Triggers	Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
This app lets me know when there is information for me	1	2	3	4	5	6	7
This app can prompt me to use it	1	2	3	4	5	6	7
This app has audible indicators	1	2	3	4	5	6	7
This app has visual indicators which can alert me	1	2	3	4	5	6	7
This app can vibrate when it has information for me	1	2	3	4	5	6	7
This app can send me alerts	1	2	3	4	5	6	7

Technology Complexity	Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
Using this app takes too much time from my normal activities	1	2	3	4	5	6	7
Working with this app is so complicated, it is difficult to understand what is going on	1	2	3	4	5	6	7
Using this app involves too much time doing mechanical operations (e.g., data input)	1	2	3	4	5	6	7
It takes too long to learn how to use this app to make it worth the effort	1	2	3	4	5	6	7

Continuance Intention	Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
My intentions are to continue using this app rather than use any alternative technology	1	2	3	4	5	6	7
I intent to continue using this app rather than use any alternative technology	1	2	3	4	5	6	7
If I could, I would like to continue my use of this app	1	2	3	4	5	6	7

Perception of Sunk Costs	Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
I feel I have invested considerable time using this app	1	2	3	4	5	6	7
I have put a lot into my use of this app	1	2	3	4	5	6	7
I have invested a great deal of effort into using this app	1	2	3	4	5	6	7
I feel I have spent a great deal of energy using this app	1	2	3	4	5	6	7
I feel I have put considerable effort into using this app	1	2	3	4	5	6	7
I feel invested in this app	1	2	3	4	5	6	7
I am aware of how much money I have spent on this app	1	2	3	4	5	6	7
The money I have spent on this app was a good investment	1	2	3	4	5	6	7
I am satisfied with the amount I paid for this app	1	2	3	4	5	6	7
The money I paid for this app was well worth it	1	2	3	4	5	6	7

Technology Habit	Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
The use of this app has become a habit for me	1	2	3	4	5	6	7
I don’t even think twice before using this app	1	2	3	4	5	6	7
Using this app has become natural to me	1	2	3	4	5	6	7
Using this app has become automatic to me	1	2	3	4	5	6	7

Technology Craving	Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
I often spontaneously think about this app	1	2	3	4	5	6	7
I sometimes feel an urge to use this app	1	2	3	4	5	6	7
I find myself thinking about this app	1	2	3	4	5	6	7
I have experienced feelings of craving associated with my use of this app	1	2	3	4	5	6	7

Compulsive Technology Use	Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
I choose this app without even being aware of making the choice	1	2	3	4	5	6	7
I unconsciously start using this app	1	2	3	4	5	6	7
Using this app is something I do without even being aware of it	1	2	3	4	5	6	7
I find myself checking in with this app without explicitly planning to do so	1	2	3	4	5	6	7
I often feel compelled to use this app	1	2	3	4	5	6	7
I often feel I spontaneously use this app	1	2	3	4	5	6	7
I feel I must use this app	1	2	3	4	5	6	7

	Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
I am currently satisfied with my relationship with my significant other	1	2	3	4	5	6	7
I currently struggle with more than one type of addictive behavior	1	2	3	4	5	6	7

Please indicate your age	**<18**	**18-21**	**22-25**	**26-34**	**35-45**	**46-54**	**>55**
	1	2	3	4	5	6	7
Please indicate your gender	**Male**	**Female**					
	1	2					
Please indicate your highest educational level attained	**Some High School**	**High School Degree**	**Some College**	**Associates Degree**	**Bachelors Degree**	**Masters Degree**	**Doctorate Degree**
	1	2	3	4	5	6	7
Please indicate your university GPA	**< 1.0**	**1.0 – 1.49**	**1.5 – 1.99**	**2.0 – 2.49**	**2.5 – 2.99**	**3.0 – 3.49**	**3.5 – 4.0**
	1	2	3	4	5	6	7

APPENDIX B

HUMAN SUBJECTS APPROVAL

Florida State
UNIVERSITY

Office of the Vice President for Research
Human Subjects Committee
Tallahassee, Florida 32306-2742
(850) 644-8673 · FAX (850) 644-4392

APPROVAL MEMORANDUM

Date: 05/15/2013

To: Jeffrey Clements [redacted]

Address: 1110

Dept.: COLLEGE OF BUSINESS

From: Thomas L. Jacobson, Chair

Re: Use of Human Subjects in Research
Mobile App Use

The application that you submitted to this office in regard to the use of human subjects in the proposal referenced above have been reviewed by the Secretary, the Chair, and two members of the Human Subjects Committee. Your project is determined to be Expedited per 45 CFR § 46.110(7) and has been approved by an expedited review process.

The Human Subjects Committee has not evaluated your proposal for scientific merit, except to weigh the risk to the human participants and the aspects of the proposal related to potential risk and benefit. This approval does not replace any departmental or other approvals, which may be required.

If you submitted a proposed consent form with your application, the approved stamped consent form is attached to this approval notice. Only the stamped version of the consent form may be used in recruiting research subjects.

If the project has not been completed by 05/14/2014 you must request a renewal of approval for continuation of the project. As a courtesy, a renewal notice will be sent to you prior to your expiration date; however, it is your responsibility as the Principal Investigator to timely request renewal of your approval from the Committee.

You are advised that any change in protocol for this project must be reviewed and approved by the Committee prior to implementation of the proposed change in the protocol. A protocol change/amendment form is required to be submitted for approval by the Committee. In addition, federal regulations require that the Principal Investigator promptly report, in writing any unanticipated problems or adverse events involving risks to research subjects or others.

By copy of this memorandum, the chairman of your department and/or your major professor is reminded that he/she is responsible for being informed concerning research projects involving human subjects in the department, and should review protocols as often as needed to insure that the project is being conducted in compliance with our institution and with DHHS regulations.

This institution has an Assurance on file with the Office for Human Research Protection. The Assurance Number is IRB00000446.

Cc: Ashley Bush [redacted], Advisor
HSC No. 2013.10509

FSU Behavioral Consent Form

You are invited to take part in a research study about how people interact with voluntary use application. Voluntary use applications are defined as mobile applications that people use by their own volition outside of the context of their jobs. Examples include programs such as Facebook, Twitter, Angry Birds, Pinterest, and Instagram. This study is being conducted by Mr. Jeffrey Clements and Dr. Ashley Bush, both of the College of Business, at Florida State University. Your help with this study will ultimately result in information that will lead to better information systems. We ask that you read this form and ask any questions you may have before agreeing to take part in the study.

Your participation is voluntary and there is no penalty if you choose to not participate. Your participation in the study is limited to completing a short survey. It should take you no more than 15 minutes to complete the survey. The survey is about your use of a voluntary use information system. Please do not write your name on the survey or otherwise provide any information that might lead to identifying you. The survey is completely anonymous, and none of your answers will be traced back to you. The completed paper surveys will be stored in a locked file cabinet in the office of Dr. Ashley Bush. Web based survey data and paper based survey data will be stored using 256 bit encryption on Mr. Jeff Clements' and Dr. Ashley Bush's computers, access to which is password protected. Data will only be reported in aggregate form further ensuring that responses cannot be tied to individual subjects.

For your participation, you will have the option to participate in a drawing for one of ten $5 Starbucks gift cards. Participation in this study is voluntary. If you decide to participate, you are free to not answer any question or withdraw at any time. Participation in the study will have no direct benefits to you, and the risks of participation should be minimal. No audio or video recording devices will be used throughout this study.

The researchers conducting this study are Mr. Jeffrey Clements and Dr. Ashley Bush. If you have any questions or concerns about the study, please raise them now. If you have a question

later, you are encouraged to contact Dr. Bush at [redacted]
Additionally you can contact Mr. Jeffrey Clements [redacted]

If you have any questions or concerns regarding this study and would like to talk to someone other than the researcher(s), you are encouraged to contact the FSU IRB at 2010 Levy Street, Research Building B, Suite 276, Tallahassee, FL 32306-2742, or 850-644-8633, or by email at humansubjects@magnet.fsu.edu.

Statement of Consent:

I have read the above information. I have been given the opportunity to ask questions, and those questions, if any, have been answered to my satisfaction. I consent to participate in the study.

__________________ __________________

Signature Date

__________________ __________________

Signature of Investigator Date

REFERENCES

Aarts, H., T. Paulussen and H. Schaalma, 1997, Physical exercise habit: On the conceptualization and formation of habitual health behaviors (Health Education Research) 363-374.

Aarts, H., B. Verplanken and A. Knippenberg, 1998, Predicting behavior from actions in the past: Repeated decision making or a matter of habit? *Journal of Applied Social Psychology* 28, 1355-1374.

Abrams, D. B., 2000, Transdisciplinary concepts and measures of craving: Commentary and future directions. *Addiction* 95, S237-246.

Adams, D. A., R. R. Nelson and P. A. Todd, 1992, Perceived usefulness, ease of use, and usage of information technology: a replication. *MIS quarterly*, 227-247.

Adams, S., 2012, Using iPads before bed 'can lead to a poor night's sleep, (The Telegraph).

Agrifoglio, R., S. Black, C. Metallo and M. Ferrara, 2012, EXTRINSIC VERSUS INTRINSIC MOTIVATION IN CONTINUED TWITTER USAGE. *Journal of Computer Information Systems* 53, 33-41.

Ajzen, I., 1981, Message-Attitude-Behavior Relationship - Theory, Methodology, and Application - Cushman,Dp, Mcphee,Rd. *Contemporary Psychology* 26, 964-966.

Ajzen, I., 1991, The theory of planned behavior, (Organizational Behavior and Human Decision Processes) 179-211.

Ajzen, I. and M. Fishbein, 1975, Belief, attitude, intention, and behavior: An introduction to theory and research, (Addison-Wesley, Reading, MA).

Ajzen, I. and M. Fishbein, 2000, Attitudes and the Attitude-Behavior Relation: Reasoned and Automatic Processes. *European Review of Social Psychology* 11, 1-33.

Al-Natour, S. and I. Benbasat, 2009, The Adoption and Use of IT Artifacts: A New Interaction-Centric Model for the Study of User-Artifact Relationships. *Journal of the Association for Information Systems* 10, 661-685.

Al-Somali, S. A., R. Gholami and B. Clegg, 2009, An investigation into the acceptance of online banking in Saudi Arabia. *Technovation* 29, 130-141.

Arkes, H. and C. Blumer, 1985, The Psychology of Sunk Cost, (Organizational Behavior and Human Decision Processes) 124-140.

Arkes, H. R., 1985, The Psychology of Sunk Cost, in: C. Blumer, ed. (Organizational Behavior and Human Decision Processes) 124-140.

Arkes, H. R. and L. Hutzel, 2000, The role of probability of success estimates in the sunk cost effect

Journal of Behavioral Decision Making Volume 13, Issue 3. *Journal of Behavioral Decision Making* 13, 295-306.

Ba, S. and P. A. Pavlou, 2002, Evidence of the effect of trust building technology in electronic markets: Price premiums and buyer behavior. *MIS quarterly*, 243-268.

Babbie, E. R., 1990, *Survey research methods* (Wadsworth Publishing Company Belmont, CA) Pages.

Bandura, A., 1977, Self-efficacy: toward a unifying theory of behavioral change. *Psychological review* 84, 191.

Bargh, J. A., M. Chen and L. Burrows, 1996, Automaticity of social behavior: Direct effects of trait construct and stereotype activation on action. *Journal of Personality and Social Psychology* 71, 230-244.

Barnes, S. J. and M. BöHringer, 2011, MODELING USE CONTINUANCE BEHAVIOR IN MICROBLOGGING SERVICES: THE CASE OF TWITTER. *Journal of Computer Information Systems* 51, 1-10.

Baron, R. M. and D. A. Kenny, 1986, The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of personality and social psychology* 51, 1173.

Bayer, J. B. and S. W. Campbell, 2012, Texting while driving on automatic: Considering the frequency-independent side of habit. *Computers in Human Behavior* 28, 2083-2090.

Bhattacherjee, A., 2001, Understanding information systems continuance: An expectation-confirmation model. *Mis Quarterly* 25, 351-370.

Bhattacherjee, A., M. Limayem and C. M. K. Cheung, 2012, User switching of information technology: A theoretical synthesis and empirical test. *Information & Management* 49, 327-333.

Bhattacherjee, A., J. Perols and C. Sanford, 2008, INFORMATION TECHNOLOGY CONTINUANCE: A THEORETIC EXTENSION AND EMPIRICAL TEST. *Journal of Computer Information Systems* 49, 17-26.

Bindley, C., 2013, Sleep Texting Is On The Rise, Experts Suggest, (Huffington Post).

Brancheau, J. C. and J. C. Wetherbe, 1987, Key issues in information systems management. *MIS quarterly*, 23-45.

Bretschneider, S. and D. Wittmer, 1993, Organizational adoption of microcomputer technology: The role of sector. *Information Systems Research* 4, 88-108.

Brown, S. A., V. Venkatesh and S. Goyal, 2012, Expectation Confirmation in Technology Use. *Information Systems Research* 23, 474-487.

Buckner V, J. E., C. M. Castille and T. L. Sheets, 2012, The Five Factor Model of personality and employees' excessive use of technology. *Computers in Human Behavior* 28, 1947-1953.

Byun, S., C. Ruffini, J. E. Mills, A. C. Douglas, M. Niang, S. Stepchenkova, S. K. Lee, J. Loutfi, J.-K. Lee, M. Atallah and M. Blanton, 2009, Internet Addiction: Metasynthesis of 1996–2006 Quantitative Research. *CyberPsychology & Behavior* 12, 203-207.

Canalys, 2012, Top 25 US developers account for half of app revenue.

Carbonell, X., E. Guardiola, M. Beranuy and A. Belles, 2009, A bibliometric analysis of the scientific literature on Internet, video games, and cell phone addiction. *J Med Libr Assoc* 97, 102-107.

Carter, M., J. A. Clements, J. Thatcher and J. George, 2011, Unraveling the "paradox of the active user": Determinants of individuals' innovation with it-based work routines, (AMCIS 2011 Proceedings - All Submissions. Paper 41.).

Cascardi, M., S. Avery-Leaf, K. D. O'Leary and A. M. S. Slep, 1999, Factor structure and convergent validity of the Conflict Tactics Scale in high school students. *Psychological Assessment* 11, 546.

Castaneda, J. A., F. Munoz-Leiva and T. Luque, 2007, Web Acceptance Model (WAM): Moderating effects of user experience. *Information & Management* 44, 384-396.

Chan, F. K. Y., J. Y. L. Thong, V. Venkatesh, S. A. Brown, P. Jen-Hwa Hu and K. Y. Tam, 2010, Modeling Citizen Satisfaction with Mandatory Adoption of an E-Government Technology. *Journal of the Association for Information Systems* 11.

Chan, K. Y., M. Gong, Y. Xu and J. Y. L. Thong, Examining user acceptance of SMS: An empirical study in China and Hong Kong, 294.

Chang, I., H.-G. Hwang, W.-F. Hung and Y.-C. Li, 2007, Physicians' acceptance of pharmacokinetics-based clinical decision support systems. *Expert Systems with Applications* 33, 296-303.

Charlton, J. P. and I. D. W. Danforth, 2010, Validating the distinction between computer addiction and engagement: online game playing and personality. *Behaviour & Information Technology* 29, 601-613.

Chau, P. Y. K. and P. J. Hu, 2002, Examining a model of information technology acceptance by individual professionals: An exploratory study. *Journal of Management Information Systems* 18, 191-230.

Chen, I. Y. L., 2007, The factors influencing members' continuance intentions in professional virtual communities - a longitudinal study. *Journal of Information Science* 33, 451-467.

Cheung, C. M. K., G. W. W. Chan and M. Limayem, 2005, A critical review of online consumer behavior: Empirical research. *Journal of Electronic Commerce in Organizations (JECO)* 3, 1-19.

Chin, W., B. Marcolin and P. Newsted, 1996, A partial least squares latent variable modeling approach for measuring interaction effects: results from a Monte Carlo simulation study and voice mail emotion/adoption study.

Chin, W. W., 1998, The partial least squares approach for structural equation modeling.

Chin, W. W., B. L. Marcolin and P. R. Newsted, 2003, A partial least squares latent variable modeling approach for measuring interaction effects: Results from a Monte Carlo simulation study and an electronic-mail emotion/adoption study. *Information Systems Research* 14, 189-217.

Chiu, C.-M., M.-H. Hsu, H. Lai and C.-M. Chang, 2012, Re-examining the influence of trust on online repeat purchase intention: The moderating role of habit and its antecedents. *Decision Support Systems* 53, 835-845.

Clark, F., K. Sanders, M. Carlson, E. Blanche and J. Jackson, 2007, Synthesis of habit theory. *OTJR: Occupation, Participation and Health* 27, 207.

Compeau, D., C. A. Higgins, S. Huff, B. P. Redesign, M. Broadbent, P. Weill, D. S. Clair, E. Karahanna, D. W. Straub and N. L. Chervany, 1999, Social Cognitive Theory and Individual Reactions to Computing Technology: A Longitudinal Study.

Costello, S., 2013, How Many Apps Are in the iPhone App Store, (www.about.com).

Csikszentmihalyi, M., 1988, The flow experience and its significance for human psychology.

Csikszentmihalyi, M., 2000, Happiness, flow, and economic equality. *Am Psychol* 55, 1163-1164.

Cutcher-Gershenfeld, J. and E. Rebentisch, 2003, The Impact of Instability on Complex Social and Technical Systems, (MIT's Engineering Systems Division External Symposium).

Davis, F., R. Bagozzi and P. Warshaw, 1989, User Acceptance of Computer Technology: A Comparison of Two Theoretical Models. *Management Science* 35, 982-1003.

Davis, R. A., G. L. Flett and A. Besser, 2002, Validation of a new scale for measuring problematic internet use: implications for pre-employment screening. *Cyberpsychol Behav* 5, 331-345.

de Guinea, A. O. and M. L. Markus, 2009, WHY BREAK THE HABIT OF A LIFETIME? RETHINKING THE ROLES OF INTENTION, HABIT, AND EMOTION IN CONTINUING INFORMATION TECHNOLOGY USE. *Mis Quarterly* 33, 433-444.

DeLone, W. H. and E. R. McLean, 1992, Information systems success: the quest for the dependent variable. *Information systems research* 3, 60-95.

Dennis, A. R., J. F. George, L. M. Jessup, J. F. Nunamaker Jr and D. R. Vogel, 1988, Information technology to support electronic meetings. *MIS quarterly*, 591-624.

Devaraj, S., M. Fan and R. Kohli, 2002, Antecedents of B2C channel satisfaction and preference: Validating e-commerce metrics. *Information Systems Research* 13, 316-333.

Fazio, R. H., 1990, Multiple processes by which attitudes guide behavior: The MODE model as an integrative framework, (Advances in Experimental Social Psychology) 75-109.

Fishbein, M. and I. Ajzen, 1981, On Construct-Validity - a Critique of Miniard and Cohen Paper. *Journal of Experimental Social Psychology* 17, 340-350.

Fornell, C. and D. F. Larcker, 1981, Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research*, 39-50.

Fortuna, J. L. D. and D. A. P. Smelson, 2008, The Phenomenon of Drug Craving. *Journal of Psychoactive Drugs* 40, 255-261.

Fowler, F. J., 2002, *Survey research methods* (Sage Publications) Pages.

Fowler Jr, F. J., 2008, *Survey research methods* (SAGE Publications, Incorporated) Pages.

Friedman, D., K. Pommerenke, R. Lukose, G. Milam and B. A. Huberman, 2007, Searching for the sunk cost fallacy. *Experimental Economics* 10, 79-104.

García-Rodríguez, O., M. Ferrer-García, I. Pericot-Valverde, J. Gutiérrez-Maldonado, R. Secades-Villa and J. L. Carballo, 2011, Identifying specific cues and contexts Related to smoking craving for the development of Effective virtual environments. *Cyberpsychology, Behavior, and Social Networking* 14, 91-97.

Garland, H. and S. Newport, 1991, Effects of absolute and relative sunk costs on the decision to persist with a course of action. *Organizational Behavior and Human Decision Processes* 48, 55-69.

Gefen, D., 2003, Assessing unidimensionality through LISREL: an explanation and an example. *Communications of the Association for Information Systems* 12, 2.

Gefen, D., 2004, TAM or Just Plain Habit. *Advanced Topics in End User Computing: Vol. 3* 3, 1.

Gefen, D., E. Karahanna and D. W. Straub, 2003, Trust and TAM in online shopping: an integrated model. *MIS quarterly*, 51-90.

Gefen, D. and D. Straub, 2005, A practical guide to factorial validity using PLS-Graph: Tutorial and annotated example. *Communications of the Association for Information Systems* 16, 109.

Gefen, D. and D. W. Straub, 1997, Gender differences in the perception and use of e-mail: An extension to the technology acceptance model. *MIS quarterly*, 389-400.

Geisser, S., 1975, The predictive sample reuse method with applications. *Journal of the American Statistical Association* 70, 320-328.

Gerbing, D. W. and J. C. Anderson, 1988, An updated paradigm for scale development incorporating unidimensionality and its assessment. *Journal of Marketing research*, 186-192.

Geron, T., 2012, Do iOS Apps Crash More Than Andriod Apps: A Data Dive, (Forbes).

Google, 2013, (www.play.google.com).

Graydian, 2013, How Mobile Apps Changed Everything, (www.graydian.com).

Gruen, T. W., J. O. Summers and F. Acito, 2000, Relationship marketing activities, commitment, and membership behaviors in professional associations. *Journal of marketing* 64, 34-49.

Guler, I., 2007, Throwing good money after bad? Political and institutional influences on sequential decision making in the venture capital industry. *Administrative Science Quarterly* 52, 248-285.

Gupta, B., S. Dasgupta and A. Gupta, 2008, Adoption of ICT in a government organization in a developing country: An empirical study. *The Journal of Strategic Information Systems* 17, 140-154.

Gupta, S. and H.-W. Kim, 2007, The moderating effect of transaction experience on the decision calculus in on-line repurchase. *International Journal of Electronic Commerce* 12, 127-158.

Hair, J. F., C. M. Ringle and M. Sarstedt, 2011, PLS-SEM: Indeed a silver bullet. *The Journal of Marketing Theory and Practice* 19, 139-152.

Hall, C. S. and G. Lindzey, 1957, Stimulus-response theory.

Hausman, A. V. and J. S. Siekpe, 2009, The effect of web interface features on consumer online purchase intentions. *Journal of Business Research* 62, 5-13.

Hayduk, L. A., 1988, *Structural equation modeling with LISREL: Essentials and advances* (JHU Press) Pages.

Hayes, A. F., 2009, Beyond Baron and Kenny: Statistical mediation analysis in the new millennium. *Communication Monographs* 76, 408-420.

Henseler, J., C. Ringle and R. Sinkovics, 2009, The use of partial least squares path modeling in international marketing. *Advances in International Marketing (AIM)* 20, 277-320.

Hevner, A. R., S. T. March, J. Park and S. Ram, 2004, Design science in information systems research. *MIS quarterly* 28, 75-105.

Hsieh, J., A. Rai and M. Keil, 2008, Understanding digital inequality: Comparing continued use behavioral models of the socio-economically advantaged and disadvantaged. *Mis Quarterly* 32, 97-126.

Hsieh, J., A. Rai, S. Petter and T. Zhang, 2012, IMPACT OF USER SATISFACTION WITH MANDATED CRM USE ON EMPLOYEE SERVICE QUALITY. *Mis Quarterly* 36, 1065-1080.

Hsu, M.-H. and C.-M. Chiu, 2004, Predicting electronic service continuance with a decomposed theory of planned behaviour. *Behaviour & Information Technology* 23, 359-373.

Inkpen, A. C. and P. W. Beamish, 1997, Knowledge, bargaining power, and the instability of international joint ventures. *Academy of management review*, 177-202.

Institute of Medicine (U.S.). Committee to Identify Strategies to Raise the Profile of Substance Abuse and Alcoholism Research., 1997a, *Dispelling the myths about addiction : strategies to increase understanding and strengthen research* (National Academy Press, Washington, D.C.) Pages.

Institute of Medicine (U.S.). Committee to Identify Strategies to Raise the Profile of Substance Abuse and Alcoholism Research., 1997b, Dispelling the myths about addiction strategies to increase understanding and strengthen research, (National Academy Press, Washington, D.C.) xvii, 218 p.

Ives, B., M. H. Olson and J. J. Baroudi, 1983, The measurement of user information satisfaction. *Commun. ACM* 26, 785-793.

Jasperson, J. S., P. E. Carter and R. W. Zmud, 2005, A comprehensive conceptualization of post-adoptive behaviors associated with information technology enabled work systems. *Mis Quarterly* 29, 525-557.

Kaganoff, E., 2011, Assessment of cue-induced nicotine craving using virtual reality: Clinical and laboratory implications, (University of Houston, United States -- Texas) 113.

Kang, Y. S., S. Hong and H. Lee, 2009, Exploring continued online service usage behavior: The roles of self-image congruity and regret. *Computers in Human Behavior* 25, 111-122.

Kavanagh, D. J., J. May and J. Andrade, 2009, Tests of the elaborated intrusion theory of craving and desire: Features of alcohol craving during treatment for an alcohol disorder. *British Journal of Clinical Psychology* 48, 241-254.

Kazdin, A. E., 2005, Parent Management Training: Treatment for Oppositional, Aggressive, and Antisocial Behavior in Children and Adolescents, (Oxford University Press, New York).

Kenny, D. A., 1979, Correlation and causality. *New York: Wiley, 1979* 1.

Khalifa, M., M. Limayem and V. Liu, 2002, Online Customer Stickiness: A Longitudinal Study. *Journal of Global Information Management (JGIM)* 10, 1-14.

Khalifa, M. and V. Liu, 2007, Online consumer retention: contingent effects of online shopping habit and online shopping experience. *European Journal of Information Systems* 16, 780-792.

Kim, D. J., D. L. Ferrin and H. R. Rao, 2009a, Trust and Satisfaction, Two Stepping Stones for Successful E-Commerce Relationships: A Longitudinal Exploration. *Information Systems Research* 20, 237-257.

Kim, G., B. Shin and H. G. Lee, 2009b, Understanding dynamics between initial trust and usage intentions of mobile banking. *Information Systems Journal* 19, 283-311.

Kim, H. W., H. C. Chan and Y. P. Chan, 2007, A balanced thinking-feelings model of information systems continuance. *International Journal of Human-Computer Studies* 65, 511-525.

Kim, R., 2011, The Iphone Effect: How Apple's phone changed everthing, www.gigaom.com.

Kim, S. S., 2009, THE INTEGRATIVE FRAMEWORK OF TECHNOLOGY USE: AN EXTENSION AND TEST. *Mis Quarterly* 33, 513-537.

Kim, S. S. and N. K. Malhotra, 2005, A longitudinal model of continued IS use: An integrative view of four mechanisms underlying postadoption phenomena. *Management Science* 51, 741-755.

Kim, S. S., N. K. Malhotra and S. Narasimhan, 2005, Research Note—Two Competing Perspectives on Automatic Use: A Theoretical and Empirical Comparison. *Information Systems Research* 16, 418-432.

Klein, J., Y. Moon and R. W. Picard, This computer responds to user frustration, (ACM) 242-243.

Kline, R. B., 2011, *Principles and practice of structural equation modeling* (Guilford press) Pages.

Lankton, N. K., D. H. McKnight and J. B. Thatcher, 2012, The Moderating Effects of Privacy Restrictiveness and Experience on Trusting Beliefs and Habit: An Empirical Test of Intention to Continue Using a Social Networking Website. *Ieee Transactions on Engineering Management* 59, 654-665.

Lankton, N. K., E. V. Wilson and E. Mao, 2010, Antecedents and determinants of information technology habit. *Information & Management* 47, 300-307.

LaRose, R., 2010, The Problem of Media Habits. *Communication Theory* 20, 194-+.

Lee, M.-C., 2009, Factors influencing the adoption of internet banking: An integration of TAM and TPB with perceived risk and perceived benefit. *Electronic Commerce Research and Applications* 8, 130-141.

Liang, H., N. Saraf, Q. Hu and Y. Xue, 2007, Assimilation of enterprise systems: the effect of institutional pressures and the mediating role of top management. *Mis Quarterly* 31, 59-87.

Liang, T.-P. and H.-J. Lai, 2002, Effect of store design on consumer purchases: an empirical study of on-line bookstores. *Information & Management* 39, 431-444.

Limayem, M. and C. M. K. Cheung, 2008, Understanding information systems continuance: The case of Internet-based learning technologies. *Information & Management* 45, 227-232.

Limayem, M., S. G. Hirt and C. M. K. Cheung, 2007, How habit limits the predictive power of intention: The case of information systems continuance. *Mis Quarterly* 31, 705-737.

MacKenzie, S. B., P. M. Podsakoff and N. P. Podsakoff, 2011, Construct measurement and validation procedures in MIS and behavioral research: integrating new and existing techniques. *MIS quarterly* 35, 293-334.

Mahoney, J. T., 2005, *Economic Foundations of Strategy* (Sage, CA) Pages.

Malhotra, N. K., S. S. Kim and A. Patil, 2006, Common method variance in IS research: A comparison of alternative approaches and a reanalysis of past research. *Management Science* 52, 1865-1883.

Manley, S. and M. Seltzer, Web facts and fantasy,   25-35.

Marcoulides, G. A., W. W. Chin and C. Saunders, 2009, A critical look at partial least squares modeling. *Mis Quarterly* 33, 171-175.

Marcoulides, G. A. and C. Saunders, 2006, Editor's comments: PLS: a silver bullet? *MIS quarterly* 30, iii-ix.

Mason, R. O. and I. I. Mitroff, 1973, A program for research on management information systems. *Management science* 19, 475-487.

Meerkerk, G. J., R. J. J. M. Van Den Eijnden, A. A. Vermulst and H. F. L. Garretsen, 2009, The Compulsive Internet Use Scale (CIUS): Some Psychometric Properties. *CyberPsychology & Behavior* 12, 1-6.

Moon, J.-W. and Y.-G. Kim, 2001, Extending the TAM for a World-Wide-Web context. *Information & Management* 38, 217-230.

Moore, G. C. and I. Benbasat, 1991, Development of an Instrument to Measure the Perceptions of Adopting an Information Technology Innovation. *Information Systems Research* 2, 192-222.

Moores, T. T., 2012, Towards an integrated model of IT acceptance in healthcare. *Decision Support Systems* 53, 507-516.

Morgan, R. M. and S. D. Hunt, 1994, The commitment-trust theory of relationship marketing. *Journal of marketing* 58.

Mottram, A. J. and M. J. Fleming, 2009, Extraversion, Impulsivity, and Online Group Membership as Predictors of Problematic Internet Use. *CyberPsychology & Behavior* 12, 319-321.

Murray, K. B. and G. HÄUbl, 2007, Explaining Cognitive Lock-In: The Role of Skill-Based Habits of Use in Consumer Choice. *Journal of Consumer Research* 34, 77-88.

Müller-Seitz, G., K. Dautzenberg, U. Creusen and C. Stromereder, 2009, Customer acceptance of RFID technology: evidence from the German electronic retail sector. *Journal of Retailing and Consumer Services* 16, 31-39.

Nan, N., 2011, CAPTURING BOTTOM-UP INFORMATION TECHNOLOGY USE PROCESSES: A COMPLEX ADAPTIVE SYSTEMS MODEL (Mis Quarterly) 505-532.

Neal, D. T., W. Wood and J. M. Quinn, 2006, Habits—A repeat performance. *Current Directions in Psychological Science* 15, 198-202.

Neufeld, D. J., L. Dong and C. Higgins, 2007, Charismatic leadership and user acceptance of information technology. *European Journal of Information Systems* 16, 494-510.

Neumann, P. G., 1998, Are computers addictive? *Communications of the ACM* 41, 128.

Niederman, F., J. C. Brancheau and J. C. Wetherbe, 1991, Information systems management issues for the 1990s. *MIS quarterly* 15, 475-500.

Nunes, J. C. and X. Dreze, 2006, The endowed progress effect: How artificial advancement increases effort. *Journal of Consumer Research* 32, 504-512.

Orford, J., *Problem gambling and other behavioural addictions* Pages.

Orford, J., 1986, Critical conditions for change in the addictive behaviors.

Orford, J., 2005, *Problem gambling and other behavioural addictions* (University) Pages.

Orlikowski, W. J. and J. J. Baroudi, 1991, Studying information technology in organizations: Research approaches and assumptions. *Information systems research* 2, 1-28.

Orlikowski, W. J. and D. Robey, 1991, Information technology and the structuring of organizations. *Information systems research* 2, 143-169.

Ouellette, J. A. and W. Wood, 1998, Habit and intention in everyday life: The multiple processes by which past behavior predicts future behavior. *Psychological Bulletin* 124, 54-74.

Oulasvirta, A., T. Rattenbury, L. Ma and E. Raita, 2012, Habits make smartphone use more pervasive. *Personal and Ubiquitous Computing* 16, 105-114.

Parra-Frutos, I., 2009, The behaviour of the modified Levene's test when data are not normally distributed. *Computational Statistics* 24, 671-693.

Paul, D. L. and R. R. McDaniel, 2004, A field study of the effect of interpersonal trust on virtual collaborative relationship performance. *Mis Quarterly* 28, 183-227.

Pavlov, I. P., 1927, Conditioned Reflexes, (Oxford Univeristy Press, London).

Perkins, N., 2012, Diminishing Distractions in a Hyper-Present World, (Urban Times).

Phillips, O. R., R. C. Battalio and C. A. Kogut, 1991, Sunk and opportunity costs in valuation and bidding. *Southern Economic Journal*, 112-128.

Pinsonneault, A. and K. L. Kraemer, 1993, Survey Research Methodology in Management Information Systems: An Assessment.

Podsakoff, P. M., S. B. MacKenzie, J.-Y. Lee and N. P. Podsakoff, 2003, Common method biases in behavioral research: a critical review of the literature and recommended remedies. *Journal of applied psychology* 88, 879.

Polites, G., 2009, The duality of habit in information technology acceptance, (The University of Georgia).

Polites, G. L. and E. Karahanna, 2012, SHACKLED TO THE STATUS QUO: THE INHIBITING EFFECTS OF INCUMBENT SYSTEM HABIT, SWITCHING COSTS, AND INERTIA ON NEW SYSTEM ACCEPTANCE. *MIS Quarterly* 36, 21-A13.

Porter, G. and N. K. Kakabadse, 2006, HRM perspectives on addiction to technology and work. *Journal of Management Development* 25, 535-560.

Ringle, C. M., S. Wende and A. Will, 2005, SmartPLS–Version 2.0. *Universitat Hamburg, Hamburg.[Links]*.

Rogers, E. M. and F. F. Shoemaker, 1971, Communication of Innovations; A Cross-Cultural Approach, (The Free Press, 866 Third Avenue, New York, N. Y. 10022 ($10.95)).

Rohsenow, D. J., P. M. Monti, A. V. Rubonis, S. B. Gulliver, S. M. Colby, J. A. Binkoff and D. B. Abrams, 2001, Cue exposure with coping skills training and communication skills training for alcohol dependence: 6- and 12-month outcomes. *Addiction* 96, 1161-1174.

Rohsenow, D. J., R. S. Niaura, A. R. Childress, D. B. Abrams and P. M. Monti, 1990, Cue reactivity in addictive behaviors: theoretical and treatment implications. *Int J Addict* 25, 957-993.

Rook, D. W. and R. J. Fisher, 1995, Normative influences on impulsive buying behavior. *Journal of Consumer Research* 22, 305-305.

Saladin, M. E., K. T. Brady, K. Graap and B. O. Rothbaum, 2006, A preliminary report on the use of virtual reality technology to elicit craving and cue reactivity in cocaine dependent individuals. *Addictive Behaviors* 31, 1881-1894.

Samuelson, W. and R. Zeckhauser, 1988, Status quo bias in decision making. *Journal of risk and uncertainty* 1, 7-59.

Sarstedt, M., J.-M. Becker, C. Ringle and M. Schwaiger, 2011, Uncovering and treating unobserved heterogeneity with FIMIX-PLS: Which model selection criterion provides an appropriate number of segments? *Schmalenbach Business Review* 63, 34-62.

Schwartz, E. I., 2001, *Digital Darwinism: 7 breakthrough business strategies for surviving in the cutthroat Web economy* (Broadway) Pages.

Schwarz, A., C. Schwarz, Y. Jung, B. Perez and S. Wiley-Patton, 2012, Towards an understanding of assimilation in virtual worlds: the 3C approach. *European Journal of Information Systems* 21, 303-320.

See-To, E. W. K., S. Papagiannidis and V. Cho, 2012, User experience on mobile video appreciation: How to engross users and to enhance their enjoyment in watching mobile video clips. *Technological Forecasting and Social Change* 79, 1484-1494.

Serenko, A., 2008, A model of user adoption of interface agents for email notification. *Interacting with Computers* 20, 461-472.

Shapira, N. A., T. D. Goldsmith, P. E. Keck Jr, U. M. Khosla and S. L. McElroy, 2000, Psychiatric features of individuals with problematic internet use. *Journal of affective disorders* 57, 267-272.

Shaw, N. G., 2002, Capturing the technological dimensions of IT infrastructure change: A model and empirical evidence. *Journal of the Association for Information Systems* 2, 8.

Shin, S.-E., N.-S. Kim and E.-Y. Jang, 2011, Comparison of Problematic Internet and Alcohol Use and Attachment Styles Among Industrial Workers in Korea. *CyberPsychology, Behavior & Social Networking* 14, 665-672.

Simon, H. A., 1947, *Administrative Behavior: a Study of Decision-Making Processes in Administrative Organization*, (Macmillan, New York).

Sivo, S. A., C. Saunders, C. Qing and J. J. Jiang, 2006, How Low Should You Go? Low Response Rates and the Validity of Inference in IS Questionnaire Research. *Journal of the Association for Information Systems* 7, 351-413.

Skinner, B. F., 1963, Behaviorism at fifty, (Science) 951-958.

Small, G., 2009, Brain Bootcamp, Exercising your most important organ, (Psychology Today).

Soong, J., 2008, When technology addiction takes over your life, (WebMD).

Spector, P. E., 2006, Method variance in organizational research truth or urban legend? *Organizational research methods* 9, 221-232.

Staw, B. M. and H. Hoang, 1995, Sunk costs in the NBA: Why draft order affects playing time and survival in professional basketball. *Administrative Science Quarterly*, 474-494.

Stone, M., 1974, Cross-validatory choice and assessment of statistical predictions. *Journal of the Royal Statistical Society. Series B (Methodological)*, 111-147.

Straub, D., M.-C. Boudreau and D. Gefen, 2004, Validation guidelines for IS positivist research. *Communications of the Association for Information Systems* 13, 380-427.

Sun, Y., A. Bhattacherjee and Q. Ma, 2009, Extending technology usage to work settings: The role of perceived work compatibility in ERP implementation. *Information & Management* 46, 351-356.

Sun, Y. Q., Y. L. Fang and K. H. Lim, 2012, Understanding sustained participation in transactional virtual communities. *Decision Support Systems* 53, 12-22.

Taylor, S. and P. A. Todd, 1995, Understanding Information Technology Usage: A Test of Competing Models. *Information Systems Research* 6, 144-176.

Thompson, R. L., C. A. Higgins and J. M. Howell, 1991, Personal computing: toward a conceptual model of utilization. *MIS Q.* 15, 125-143.

Tiwana, A. and A. A. Bush, 2005, Continuance in expertise-sharing networks: A social perspective. *Ieee Transactions on Engineering Management* 52, 85-101.

Tiwana, A. and M. Keil, 2007, Does peripheral knowledge complement control? An empirical test in technology outsourcing alliances. *Strategic Management Journal* 28, 623-634.

Tokunaga, R. S. and S. A. Rains, 2010, An Evaluation of Two Characterizations of the Relationships Between Problematic Internet Use, Time Spent Using the Internet, and Psychosocial Problems. *Human Communication Research* 36, 512-545.

Triandis, H. C., 1971, Attitude and Attitude Change. *John Wiley and Sons* New York.

Tudor, A., 2013, Why the relationship between people and mobile apps matters, (Appscend.com).

Turel, O. and A. Serenko, 2010, Is Mobile Email Addiction Overlooked? *Communications of the ACM* 53, 41-43.

Turel, O. and A. Serenko, 2012, The benefits and dangers of enjoyment with social networking websites. *European Journal of Information Systems* 21, 512-528.

Turel, O., A. Serenko and P. Giles, 2011a, INTEGRATING TECHNOLOGY ADDICTION AND USE: AN EMPIRICAL INVESTIGATION OF ONLINE AUCTION USERS. *Mis Quarterly* 35, 1043-1061.

Turel, O., A. Serenko and P. Giles, 2011b, INTEGRATING TECHNOLOGY ADDICTION AND USE: AN EMPIRICAL INVESTIGATION OF ONLINE AUCTION USERS. *MIS Quarterly* 35, 1043-A1018.

Vatanasombut, B., M. Igbaria, A. C. Stylianou and W. Rodgers, 2008, Information systems continuance intention of web-based applications customers: The case of online banking. *Information & Management* 45, 419-428.

Venkatesh, V., S. A. Brown, L. M. Maruping and H. Bala, 2008, Predicting different conceptualizations of system use: the competing roles of behavioral intention, facilitating conditions, and behavioral expectation. *MIS Q.* 32, 483-502.

Venkatesh, V. and F. D. Davis, 1996, A Model of the Antecedents of Perceived Ease of Use: Development and Test*. *Decision Sciences* 27, 451-481.

Venkatesh, V. and S. Goyal, 2010, EXPECTATION DISCONFIRMATION AND TECHNOLOGY ADOPTION: POLYNOMIAL MODELING AND RESPONSE SURFACE ANALYSIS. *Mis Quarterly* 34, 281-303.

Venkatesh, V., J. Y. L. Thong and X. Xu, 2012a, CONSUMER ACCEPTANCE AND USE OF INFORMATION TECHNOLOGY: EXTENDING THE UNIFIED THEORY OF ACCEPTANCE AND USE OF TECHNOLOGY. *MIS Quarterly* 36, 157-178.

Venkatesh, V., M. Morris, G. Davis and F. Davis, 2003, User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly* 27, 425-478.

Venkatesh, V., J. Thong and X. Xu, 2012b, Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS quarterly* 36, 157-178.

Verplanken, B., 2006, Beyond frequency: Habit as mental construct. *British Journal of Social Psychology* 45, 639-656.

Verplanken, B. and H. Aarts, 1999, Habit, attitude, and planned behaviour: is habit an empty construct or an interesting case of goal-directed automaticity? *European review of social psychology* 10, 101-134.

Verplanken, B. and S. Orbell, 2003, Reflections on Past Behavior: A Self-Report Index of Habit Strength1. *Journal of Applied Social Psychology* 33, 1313-1330.

Walczuch, R., J. Lemmink and S. Streukens, 2007, The effect of service employees' technology readiness on technology acceptance. *Information & Management* 44, 206-215.

Wells, J. D., V. Parboteeah and J. S. Valacich, 2011, Online Impulse Buying: Understanding the Interplay between Consumer Impulsiveness and Website Quality*. *Journal of the Association for Information Systems* 12, 32-56.

Wood, W., J. M. Quinn and D. A. Kashy, 2002, Habits in everyday life: Thought, emotion, and action. *Journal of Personality and Social Psychology* 83, 1281-1297.

Yellowlees, P. M. and S. Marks, 2007, Problematic Internet use or Internet addiction? *Computers in Human Behavior* 23, 1447-1453.

Yi, M. Y., J. D. Jackson, J. S. Park and J. C. Probst, 2006, Understanding information technology acceptance by individual professionals: Toward an integrative view. *Information & Management* 43, 350-363.

Yoon, C., 2011, Theory of Planned Behavior and Ethics Theory in Digital Piracy: An Integrated Model. *Journal of Business Ethics* 100, 405-417.

Young, K. S., What makes on-line usage stimulating? Potential explanations for pathological Internet use.

Young, K. S., 1998, Internet addiction: The emergence of a new clinical disorder. *CyberPsychology & Behavior* 1, 237-244.

Young, K. S., C. N. d. Abreu and ebrary Inc., 2011, Internet addiction a handbook and guide to evaluation and treatment, (John Wiley & Sons, Hoboken, N.J.) 1 online resource.

Zhao, L. and Y. B. Lu, 2012, Enhancing perceived interactivity through network externalities: An empirical study on micro-blogging service satisfaction and continuance intention. *Decision Support Systems* 53, 825-834.

Zhao, X., J. G. Lynch and Q. Chen, 2010, Reconsidering Baron and Kenny: Myths and truths about mediation analysis. *Journal of Consumer Research* 37, 197-206.

Zhou, T., 2013, Understanding continuance usage of mobile services. *International Journal of Mobile Communications* 11, 56-70.

Zhou, Z. Y., Y. L. Fang, D. R. Vogel, X. L. Jin and X. Zhang, 2012, Attracted to or Locked In? Predicting Continuance Intention in Social Virtual World Services. *Journal of Management Information Systems* 29, 273-305.

Åstebro, T., 2004, Sunk costs and the depth and probability of technology adoption. *The Journal of Industrial Economics* 52, 381-399.

BIOGRAPHICAL SKETCH

Jeffrey A. Clements

Department of Management, College of Business, Florida State University

Education

Ph.D. Business Administration, Florida State University, 2010 - 2014

Dissertation title: "**Compulsive Technology Use**" Defense date –April 4, 2014.

Primary Area: Management Information Systems

Support Area: Organizational Behavior/ Human Resources Management

M.S. Information Systems, University of Utah, 2010.

B.S. Business Entrepreneurship, University of Utah, 2008.

Employment History

August, 2010 – present Research/Teaching Assistant, College of Business, Florida State University.

August, 2009 – July, 2010 Research/Teaching Assistant, College of Business, University of Utah.

January, 2005 – July, 2010 Network Operations/Desktop Support, Sorenson Communications.

RESEARCH

Peer Reviewed Journal Publications

Clements, J. A. (2012) *Remote Influence Tactics*. Computer Technology and Application, vol. 3, issue 9, pg 642-648.

Clements, J. A., & Clements, C. S. (2013) *Confident Deception: The Role of Justification*. International Journal of Psychology and Behavioral Science, vol. 3, number 6.

Textbook Publications

Bolye, R. J., & **Clements, J. A**. (2013) *Applied Networking Labs, A Hands-On Guide to Networking and Server Management*, Second Edition, Prentice Hall.

Peer Reviewed Conference Publications

Clements, J. A. (2013) *Platform-enabled Ambidexterity.* Proceedings of the 2013 Annual Meeting of the Southern Association of Information Systems (SAIS), Savannah, GA.

Proudfoot, J. G., Boyle, R. J., **Clements, J. A.** (2013) *Mitigating Threats to Collaboration and CMC: Identifying Antecedents of Online Deviance*. Proceedings of the 46th Annual Hawaii International Conference on System Sciences (HICSS).

Boyle, R. J., **Clements, J. A**., Proudfoot, J. G. (2012) *Predicting Deceptive Behavior: Exploring Antecedents to Deceptive Behaviors.* Proceedings of the National Communication Association (NCA) 98th Annual Convention, Orlando, FL.

Clements, J. A., Bush, A.A. (2011a) *Habitual IS Use.* Proceedings of the 2011 Annual Meeting of the Southern Association of Information Systems (SAIS), Atlanta, GA.

Clements, J.A., Bush, A.A. (2011b) *Perceptions of Sunk cost on Habitual IS Use.* Proceedings of the 17th Americas Conference on Information Systems (AMCIS), Detroit, MI.

Carter, M., **Clements, J.A**., Thatcher, J., & George, J. (2011). *Unraveling the "Paradox of the Active User":Determinants of Individuals' Innovation with IT-based work routines.* Proceedings of the 17th Americas Conference on Information Systems (AMCIS), Detroit, MI.

In Process

Clements, J. A., *Beyond Habit: The Role of Sunk Costs on Developing Automatic IS Use Behaviors*.

Boyle, R. J., **Clements, J. A**., & Proudfoot, J. G. *Predicting deception behavior: Exploring antecedents to deceptive behaviors.*

Clements, J. A., Boyle, R. J., & Proudfoot, J. G. *Those Dirty Politicians: Exploring Politically Motivated Intent to Deceive.*

Proudfoot, J. G., Boyle, R. J., & **Clements, J. A**. *Mitigating threats to collaboration and CMD: Identifying antecedents of online deviance.*

TEACHING

Undergraduate Courses Taught

Introduction to Management Information Systems, Florida State University,

Summer 2011, Summer 2012, Summer 2013

Business Data Networks and Telecommunications, Florida State University,

Fall 2012, Spring 2013, Fall 2013, Spring 2014

Online Graduate (MBA) Courses Taught

Knowledge Management / Business Intelligence, Florida State University (online),

Summer 2013

Information & Technology Management, Florida State University (online),

Summer 2013

SERVICE

Professional Affiliations

Association of Information Systems (AIS)

National Communication Association (NCA)

Professional Activities

Ad hoc reviewer for

- International Conference on Information Systems, Milan, Italy, 2013
- International Conference on Information Systems, Orlando, Florida, 2012
- International Conference on Information Systems, Beijing, China, 2011
- Americas Conference on Information Systems, Detroit, Michigan, 2011
- Transactions on Management Information Systems (TMIS), 2011
- European Conference on Information Systems, Helsinki, Finland 2011