Fall 2015

Employee Behavioral Intention and Technology Use: Mediating Processes and Individual Difference Moderators

Robert Conrad Brusso
Old Dominion University, rcbrusso@gmail.com

EMPLOYEE BEHAVIORAL INTENTION AND TECHNOLOGY USE:

MEDIATING PROCESSES AND INDIVIDUAL DIFFERENCE MODERATORS

by

Robert Conrad Brusso
B.S., May 2007, Virginia Polytechnic Institute and State University
M.S., December 2010, Old Dominion University

A Dissertation Submitted to the Faculty of
Old Dominion University in Partial Fulfillment of the
Requirements for the Degree of

DOCTOR OF PHILOSOPHY

PSYCHOLOGY

OLD DOMINION UNIVERSITY

December 2015

Approved by:

_____

Richard N. Landers, Ph.D.

(Director)

_____

James M. Henson Ph.D.

(Member)

_____

Pilar Pazos-Lago Ph.D.

(Member)

ABSTRACT

EMPLOYEE BEHAVIORAL INTENTION AND TECHNOLOGY USE: MEDIATING PROCESSES AND INDIVIDUAL DIFFERENCE MODERATORS

Robert Conrad Brusso
Old Dominion University, 2015
Director: Dr. Richard N. Landers

Considering the substantial amount of time and organizational resources that are involved in the development and implementation of end-user technology (e.g., communication software platforms, social networking sites) within organizations, it is imperative to understand the factors that best predict use of end-user software. Although technology acceptance models, grounded in broader theories of behavior, do exist, these models fall-short in determining the most proximal antecedents of actual behavior. Currently, the majority of the research in the information technology arena posits behavioral intention as the most proximal antecedent of technology use. Behavioral intention does explain variance in use, but this relationship has been the subject of discussions and research calling for 1) an investigation of potential moderators based on meta-analytic results, 2) the consideration of theoretically meaningfully mediators that may explain the relationship between behavioral intention and behavior, and 3) stronger experimental designs that do not rely on self-reported technology use. To this end, a model was developed that posited that the relationship between behavioral intention and behavior is mediated by implementation plans. Further, it was also hypothesized that the behavioral intention to implementation plans relationship, as well as the implementation plans to behavior relationship, is moderated by computer self-efficacy. To test the hypotheses, approximately 406 participants from a large international organization responded to survey questions intended to assess their behavioral intentions,

implementation plans, and computer self-efficacy. Further, participant usage of the

technology in question (Microsoft Lync) was assessed by querying their actual use

following a one month post-survey lag. The results demonstrated partial support for the

complete hypothesized model, with implementation plans mediating the behavioral

intentions – behavior relationship. The moderating effect of computer self-efficacy was

not supported. Practical implications, directions for future, and limitations are discussed.

This dissertation is dedicated to my grandparents who are no longer with us. Your

sacrifices made my successes possible. Grandpa Fred, Grandpa Stuart, and Grandma

Esther, you are missed very much.

ACKNOWLEDGMENTS

Although it would be easy to say that my achievements are a testament to my persistence, such a statement would do a great disservice to all of those who helped me along the way. Their support, encouragement, and total belief in my success enabled me to persist and never give up.

To my Mom and Dad, thank you for always believing in me, even when I didn't believe in myself. I know that you both want to read the entire manuscript, but if you only take one thing away from my dissertation, realize that I am eternally grateful for everything that you have ever done for me. Carrie and Ashley, thank you for pretending to care about/understand my random think-out-loud questions involving theory, experimental design, and statistical analyses when you were brave enough to ask me how I was doing. Although you may have been unable to provide me with answers, your support was just as useful. To my Grandma Hazel, you have never hesitated to tell me how proud you are of me. I finally feel like I've done something worthy of such praise.

To my friends, thank you for encouraging me to continue, taking an interest in the process, and dealing with the times where I was absent from numerous social gatherings. To my ODU colleagues, I feel very fortunate to have taken this journey with you. A special thank you to Kristina Bauer who has graciously served as my on-call dissertation consultant for the past three years.

Although losing an advisor and changing to a new one mid-way through a Ph.D. program is a unique occurrence, I feel I benefited greatly from such a circumstance. Dr. Karin Orvis, played an enormous role in my early graduate career. I believe she is largely responsible for my admission to the program and I cannot thank her enough. Dr.

Richard Landers was brave enough to adopt a lab of students following Dr. Orvis' departure. Although it took time to build a relationship with a new advisor, I owe the quality of my work to Dr. Landers. His understanding of experimental design and statistical analysis and general enthusiasm for theoretical research and technology in the workplace is contagious and I feel especially lucky that a unique circumstance gave me the opportunity to have him advise the second half of my graduate career.

I would also like to thank both of my committee members, Dr. Pilar Pazos-Lago and Dr. Matt Henson. Dr. Pazos-Lago's valuable insights have undoubtedly strengthened this manuscript and I thank her for this. I have been fortunate enough to have Dr. Henson serve on my thesis and dissertation committee. I owe my attraction to and understanding of statistical analyses to his ability to motivate students and articulate complex concepts.

I'd like to thank the department's office staff, Mary, Peggy, and Linda, for their truly remarkable commitment to the department and to helping graduate students navigate the sea of paperwork and red tape. Your assistance, support, and kindness too often go unappreciated.

Finally, I would like to thank Haley Rugh. Haley has had a front row seat to the entire dissertation process. She witnessed all of the ups and downs typical with the process (as well as my sometimes less than stellar responses to the downs) and, for some reason, stuck around. She was always there when I needed feedback on an idea, a good laugh, or simply someone to tell me I'm going to do it. You're unsolicited "I'm proud of you" statements were the fuel that kept me going throughout many sleepless nights.

Guinness, if you're reading this, your days of eating my homework have come to an end.

TABLE OF CONTENTS

Page

LIST OF TABLES

LIST OF FIGURES

CHAPTER I

INTRODUCTION

Across public, private, government, and educational organizations, the use of computer-based technology to support work and organizational processes continues to increase at a rapid rate. Recent estimates from the American Society of Training and Development (ASTD) state that organizations spent roughly $64.4 billion dollars on technology-based training and development programs alone, representing more than one third of all training and development expenditures in 2012 (Miller, Mandzuk, Frankel, McDonald, & Bello, 2013). Regarding telework, Lister and Harnish (2011) reported that approximately 45% of the U.S. workforce are permitted by their employers to telework part-time. Such employees depend on multiple forms of computer-based technology. Recent reports also indicate that about 50% of all U.S. companies use some form of social software (e.g., social networking sites, instant messengers, wikis, blogs, and internal discussion forums) (McAfee, 2011).

However, many implementations of new technology are considered failures and such failures have numerous causes (Devaraj & Kohli, 2003; Jasperson, Carter, & Zmud, 2005; Venkatesh & Bala, 2008). One common failure is low user acceptance, where user acceptance is defined as positive attitudes toward the technology system or tool (Brown & Charlier, 2013; Davis, 1989; Davis, Bagozzi, & Warshaw, 1989; Venkatesh, 2000; Venkatesh & Bala, 2008; Venkatesh & Davis, 1996; Venkatesh & Davis, 2000; Venkatesh, Morris, Davis, & Davis, 2003). Because acceptance predicts use, defined as employee work-related interaction with the technology, and subsequently influences the

---

The *Journal of Applied Psychology* was used as the journal model for this manuscript.

success of organizational technology adoption and implementation, exploration of the

antecedents of user acceptance constitutes a large research area in the study of

management information systems (Davis et al., 1989; Venkatesh & Davis, 2000;

Venkatesh et al., 2003). Interestingly, research attempting to tease out the manner in

which acceptance influences use has received little attention. Most researchers consider

the use of a technology system as de facto evidence of user acceptance (Arunkumar,

2008; Davis et al., 1989), suggesting that lack of use is indicative of non-acceptance.

However, assuming that acceptance is the only (or primary) variable with a direct effect

upon use appears to have resulted in a myopic quest to improve user acceptance at the

expense of identifying and explicating other potential antecedents of use.

Behavioral Intention and Technology Use

In prominent technology acceptance and use models, the relationships between all

individual or environmental antecedents and use are mediated by behavioral intention,

defined as the strength of an individual's desire to perform a behavior (Davis et al., 1989;

Fishbein & Ajzen, 1975; Venkatesh & Bala, 2008; Venkatesh et al., 2003), which is

intended to capture "acceptance-like" processes (Davis, 1989; Davis et al., 1989;

Dwivedi, Rana, Chen, & Williams, 2011; Venkatesh, 2000; Venkatesh & Bala, 2008;

Venkatesh & Davis, 1996; Venkatesh & Davis, 2000; Venkatesh et al., 2003). Research

on these models has supported the relationship between behavioral intention (i.e.,

acceptance) and use (Davis, 1989; Davis et al., 1989; Dwivedi et al., 2011; Venkatesh,

2000; Venkatesh & Bala, 2008; Venkatesh & Davis, 1996; Venkatesh & Davis, 2000;

Venkatesh et al., 2003), and as a result, most modern technology acceptance research

have focused narrowly upon predicting behavioral intention in order to subsequently impact use.

Although the primary framework for technology acceptance and use research are based on classic behavioral theories (i.e., the Theory of Reasoned Action, the Theory of Planned Behavior; see Ajzen, 1991; Fishbein & Ajzen, 1975), these research efforts have been dominated by an information technology perspective (Davis, 1989; Davis et al., 1989; Venkatesh & Bala, 2008; Venkatesh et al., 2003). Specifically, the goal of this stream of research has largely focused on understanding behavioral intention to use a technology to assist in the technology development process. If developers can determine appropriate system characteristics to maximize user behavioral intentions as early as possible, then the technology is likely to see greater use. However, this focus paints an incomplete picture of the process of transforming behavioral intentions into behavior.

Implementation Plans, Self-Regulation, & Technology Use

Because behavioral intention is motivational by definition (i.e., a "desire"), a volitional mechanism (such as planning related to the implementation of behavioral intentions) is necessary to transform these motivations into behavior (Sniehotta, 2005). However, such a process is missing across technology acceptance models and is a major gap in this research literature. One potential volitional construct that might be used to bridge this gap between behavioral intentions/acceptance and use is implementation plans (also known as implementation intentions), defined as behavioral plans about the "when, where, and how" of behavior (Brandstätter, Lengfelder, & Gollwitzer, 2001; Gollwitzer, 1993, 1999; Gollwitzer & Brandstätter, 1997; Gollwitzer & Sheeran, 2006; Rise, Thompson, & Verplanken, 2003; Sheeran & Silverman, 2003; Webb & Sheeran, 2008).

Specifically, an implementation plan is an "action plan," typically in the form of an "if–then plan" that specifies a behavior to be performed in response to an anticipated situational cue; it is subordinate to the related goal intention (Gollwitzer, 1993, 1999). Whereas a behavioral intention merely specifies a desire or intention to engage in an activity (e.g., "I intend to use my organization's new social media tool."), implementation plans are the action plans specifying how an individual plans to ensure the behavioral intention is converted into a behavior (e.g., "When staffing for a new project, I will search the social media site to find the best person based on their listed qualifications.") (Parks-Stamm, Gollwitzer, & Oettingen, 2007).

Implementation plans serve as a self-regulatory strategy encompassing regulation of cognitions, behaviors, and motivations. Similar self-regulatory strategies are common in goal-setting research (Latham & Locke, 2007). Researchers have described self-regulation as a system that is comprised of processes that serve to engender goal achievement (Boekaerts, Maes, & Karoly, 2005; Karoly, 1993; Sitzmann & Ely, 2011). For example, when pursuing goals, goal striving strategies (e.g., formulating action plans, maintaining effort and motivation, inhibiting off-task thoughts) are indicative of self-regulation and are of paramount importance for the achievement of goals (Boekaerts, Pintrich, & Zeidner, 2000; Brusso & Orvis, 2013; P. R. Pintrich, 2004). Thus, leveraging what is known regarding self-regulation and implementation plans will aid in understanding the relationship between behavioral intention and technology use.

If implementation plans are the driving force behind the effect of behavioral intentions on behavior (i.e., a self-regulatory strategy that engenders use), individuals may vary in their ability to develop implementation plans (Latham, Winters, & Locke,

1994; Wood & Bandura, 1989). Additionally, individuals may also vary in their ability to act upon these self-regulatory strategies (i.e. implementation plans) and translate their implementation plans into behavior (Oettingen, Wittchen, & Gollwitzer, 2013; Wieber, Odenthal, & Gollwitzer, 2010). Such variables and their ability in predicting implementation plans and augmenting the effect of implementation plans on behavior are likely to explain additional variance in actual use and should be explored.

Technology Use: Moving Forward

The relationship between the behavioral intention to use technology and actual use still requires exploration to rectify the high level of focus on behavioral intention, otherwise known as the "bottleneck" problem (Sniehotta, 2009). The key gap in the literature is the failure to consider additional mediating and moderating processes between the behavioral intention to behavior relationship. Thus, the goals of this dissertation are two-fold.

The first goal of this research effort is to empirically test the hypothesis that implementation plans (a self-regulatory strategy) mediates the effect of behavioral intention on technology use. Although behavioral intention is indicative of a motivational process, it represents an evaluation of intent at only one point in time. A volitional component that captures the effect of behavioral intention is likely a better predictor of actual behavior (Brandstätter et al., 2001; Gollwitzer, 1993, 1999; Gollwitzer & Sheeran, 2006; Sniehotta, 2009; Sniehotta, Schwarzer, Scholz, & Schüz, 2005).

The second goal of this research is to identify individual difference variables that moderate the relationship between behavioral intention and behavior. Although numerous

studies have attempted to identify the causal relationships between antecedents of

behavioral intention, behavioral intention, and actual behavior, a large portion of variance

in usage behavior is still left to be explained (Webb & Sheeran, 2006). In their meta-

analysis of the intention-behavior relationship, Webb and Sheeran (2006) found

significant variation in effect sizes between behavioral intention and behavior, suggesting

the presence of moderators. Thus, the current research literature's focus on behavioral

intention as the focal outcome ignores individual differences that may predict behavior

subsequent to the effect of behavioral intention.

Below, I present a review of prominent technology acceptance models to

highlight the strengths and weaknesses of each model. Following this review, a

hypothesized model is proposed integrating the constructs of implementation plans and

computer self-efficacy in the behavioral intention – behavior relationship.

Review of Technology Acceptance Models

Although multiple models of technology acceptance have been proposed, the

most prominent are TAM (Davis, 1985; Davis et al., 1989), TAM2 (a revision of TAM)

(Venkatesh & Davis, 2000), and UTAUT (Venkatesh et al., 2003). These technology

acceptance models share several features because of commonalities in their origins; these

models have all been adapted from the Theory or Reasoned Action (TRA, Figure 1)

(Fishbein & Ajzen, 1975) and the Theory of Planned Behavior (TPB, Figure 2) (Ajzen,

1985, 1991). Specifically, behavioral intention serves as the predictor of use across all of

these models. Although these models attempt to address the shortcomings of previous

work as the area of technology acceptance research advances, limitations still exist.

Thus, an overview of TRA and TPB as the theoretical foundation for these models is

provided below, followed by a discussion of modern technology acceptance models (in ascending chronological order; TAM, TAM2, and UTAUT, respectively) with a focus on model constructs, strengths, and weakness/issues. This section concludes with a discussion of key takeaways to highlight key gaps in understanding technology use by employees.

Theoretical Foundations. Ajzen (1991) stated that the goal of TRA was to provide an explanation for behavior in situations where individuals possess complete volitional control. In contrast, the development of TPB as an extension of TRA allowed for the prediction of behaviors with incomplete volitional control. Specifically, TPB added consideration of insufficient resources or opportunities to engage in a behavior successfully (Ajzen, 1991). However Ajzen summarized the role of behavioral intention in both models by specifying that a "behavioral intention can find expression in behavior only if the behavior in question is under volitional control," (1991, p. 182). Thus, the notion of free will to engage in the behavior is part of both models.

```
┌──────────────┐
│ Attitude Toward │
│   Behavior   │ ╲
└──────────────┘   ╲       ┌────────────┐       ┌──────────┐
                    ╲──────▶│ Behavioral │──────▶│ Behavior │
                    ╱       │  Intention │       └──────────┘
┌──────────────┐   ╱        └────────────┘
│ Subjective Norm │ ╱
└──────────────┘
```
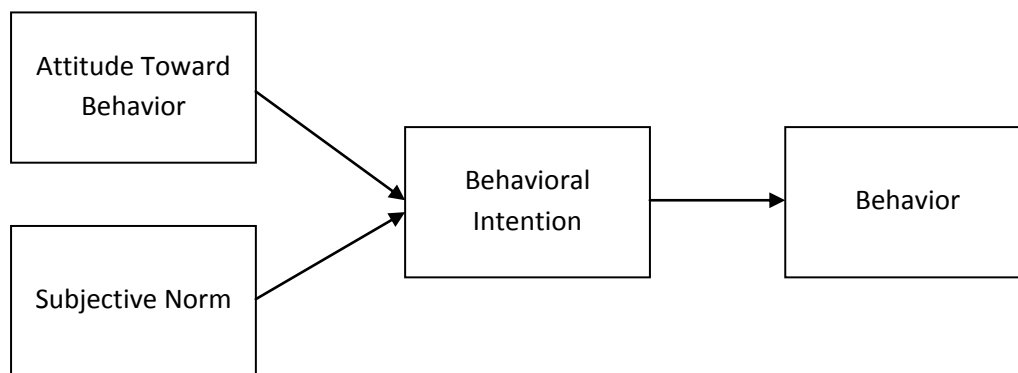
Figure 1. Theory of Reasoned Action (Fishbein & Ajzen, 1975)
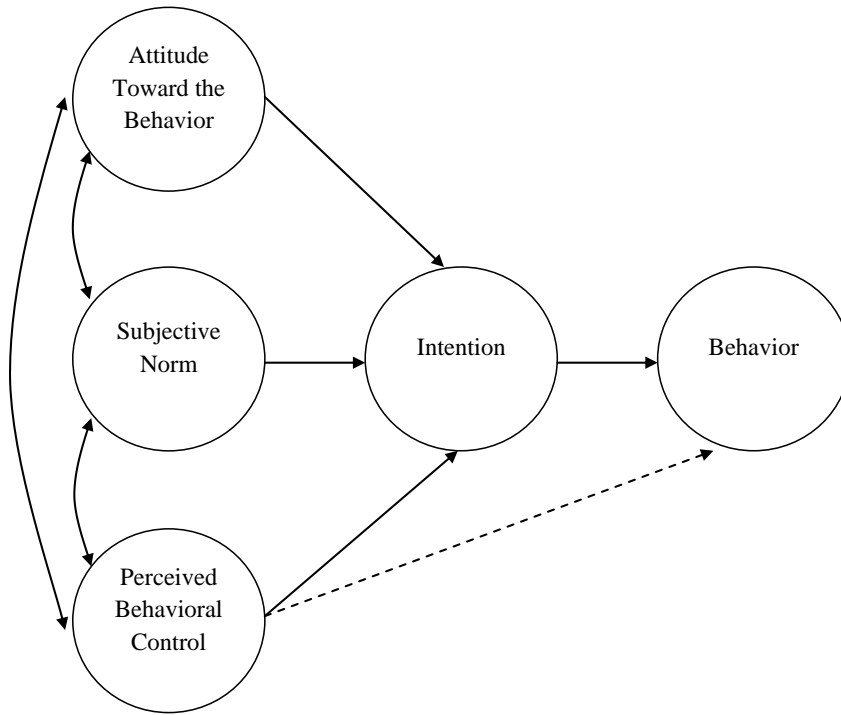
Figure 2. Theory of Planned Behavior (Ajzen, 1991)

Behavioral intention plays a crucial role in both models (TRA and TPB) because

all predictors of behavior indirectly influence behavior via their direct effect on

behavioral intention. TRA and TPB state that a behavioral intention is formed through a

process of mental deliberation that includes the evaluation of salient beliefs related to the

behavior and the formation of attitudes (Ajzen, 1985, 1991; Fishbein & Ajzen, 1975).

Thus, Fishbein and Ajzen (1975) posit that an individual's behavioral intention is

influenced, and susceptible to change, primarily through beliefs surrounding the behavior

in question. These beliefs and respective belief evaluations form the attitudes that lead to

a final determination of whether or not an individual intends to perform a behavior. In

the context of technology acceptance, if behavioral intention is the most proximal

antecedent of behavior and behavioral intention is influenced by beliefs regarding the

behavior in question, the influence of beliefs on behavior must be investigated to improve use.

Technology Acceptance Model (TAM). The Technology Acceptance Model (see Figure 3) is one of the earliest models of technology acceptance (Lee, Kozar, & Larsen, 2003). The impetus behind the development of TAM was the paucity of work related to predicting end-user use. Technology use research prior to the development of TAM had focused solely on the objective performance criteria of end-user systems, defined as any computer mediated environment (e.g., social network, knowledge portal, e-learning module) used by organizational members (Davis, 1985; Davis et al., 1989). Thus, the purpose of the model was to explain the relationship between users' perceptions of an end-user system and actual system use to demonstrate the importance of end-user system characteristics as they impact perceptions (Davis, 1985). Organizational members use these end-user systems directly and at their own discretion in order to support some work activity or function (Davis, 1985), thus understanding how perceptions impact use was a valuable direction for technology acceptance research.

Davis (1985) posited that an integration of system-design characteristics, perceptions of these characteristics, and attitudes that emerge as a result of these perceptions, would explain differences in technology acceptance. Thus, TAM was intended to capture user motivation, comprised of cognitive and affective processes, to use a technology (Davis, 1985; Davis et al., 1989).
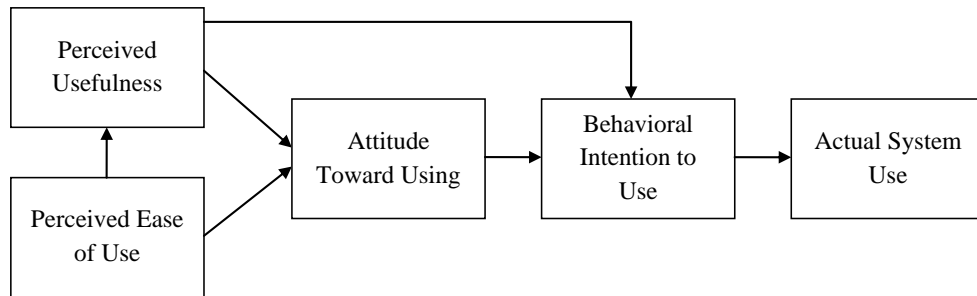
Figure 3. Technology Acceptance Model (Davis et al., 1989)

Davis et al. (1989) developed TAM beyond the original TRA and TBP structure by specifying antecedents of attitude towards using a system. Whereas attitudes in TRA are formed by a summed belief-evaluation term, TAM represents two beliefs separately (i.e., perceived usefulness and perceived ease of use) (Davis, 1985, 1989; Davis et al., 1989). From an information systems perspective, discerning the particular causal antecedents of attitude that can be manipulated to improve acceptance is of paramount importance.

The first of these beliefs posited to influence attitude toward use is perceived usefulness, which is defined as a user's perception of the likelihood that system use will result in increased performance within an organizational context (Davis et al., 1989). According to TAM, individuals who perceive that a system has some value (e.g., believing it likely to increase some facet of job performance) are more likely to express positive evaluations toward the system. Subsequently, these evaluations should result in positive attitudes. Additionally, an individual's estimation of system perceived usefulness was posited to not only indirectly influence behavioral intention, via the mediating variable of attitude toward use, but to also have a direct impact on behavioral intention (Davis, 1985, 1989; Davis et al., 1989).

The second of these beliefs theorized to influence attitude toward use, perceived ease of use, is defined as the user's perception of the level of effort required to use the system in question (Davis et al., 1989). TAM states that perceived ease of use is distinct from, but related to, perceived usefulness. Specifically, although perceived ease of use explains unique variance in behavioral intention, its effect is partially mediated by perceived usefulness; individuals who believe a system is easy to use are likely to find a system more useful than individual who perceive the system is difficult to use (Davis, 1985, 1989; Davis et al., 1989).

Empirical research has demonstrated that perceived usefulness and perceived ease of each account for significant variance in behavioral intention (King & He, 2006; Lee et al., 2003; Venkatesh & Davis, 2000). For example, Schepers and Wetzels (2007) meta-analyzed the relationships between behavioral intention and these two beliefs, concluding that these constructs accounted for 48% of the variance in behavioral intention. Lee et al. (2003), in their review of 101 TAM studies, found significant relationships between perceived ease of use and behavioral intention in 58 studies (out of 82 applicable studies) and perceived usefulness and behavioral intention in 74 studies (out of 84 applicable studies), concluding that these two constructs explain between 30% - 40% of variance in intention. Examination of the relationship between behavioral intention and behavior was less common ($k = 15$). This relative paucity of research investigating the relationship between behavioral intention and actual behavior highlights the somewhat myopic focus on predicting behavioral intention, the typical criterion of interest in TAM research. The shortcomings of such research efforts involve both the assumption that the relationship

between behavioral intention and behavior is a foregone conclusion and that behavioral intention is the only construct with a direct effect upon use.

Technology Acceptance Model 2 (TAM2). The Technology Acceptance Model 2 (TAM2) shown in Figure 4 is an extension of TAM and was developed with two purposes. First, researchers sought to resolve the shortcomings of TAM as outlined by Davis (1989) and Venkatesh (Venkatesh, 1999; Venkatesh & Davis, 1996). Specifically, TAM2 removed attitude toward use, as the results of the empirical validation of TAM showed that this construct offered little in the explanation of behavioral intentions when considering the effects of perceived ease of use and perceived usefulness (Davis, 1989; Venkatesh, 1999; Venkatesh & Davis, 1996; Venkatesh & Davis, 2000). Second, TAM2 included additional antecedents of perceived usefulness, an antecedent of behavioral intention, narrowing the focus of the model squarely on explaining behavioral intention. Empirical research has demonstrated TAM2's effective prediction of an individual's behavioral intention to use a system and system use. Venkatesh and Davis (2000) demonstrated, pooling across four studies and three time periods (n = 468), that the social and cognitive process variables shown in Figure 4 explained approximately 51% of the variance in perceived usefulness. Further, the authors demonstrated that the overall model explained approximately 49% of the variance in behavioral intention. Although R^2 values for the relationship between behavioral intention and behavior (self-reported usage of the technology in question) were not reported, the pooled results demonstrated a statistically significant relationship between behavioral intention and use. Correlations between behavioral intention and behavior across all four studies ranged from .45 - .50.
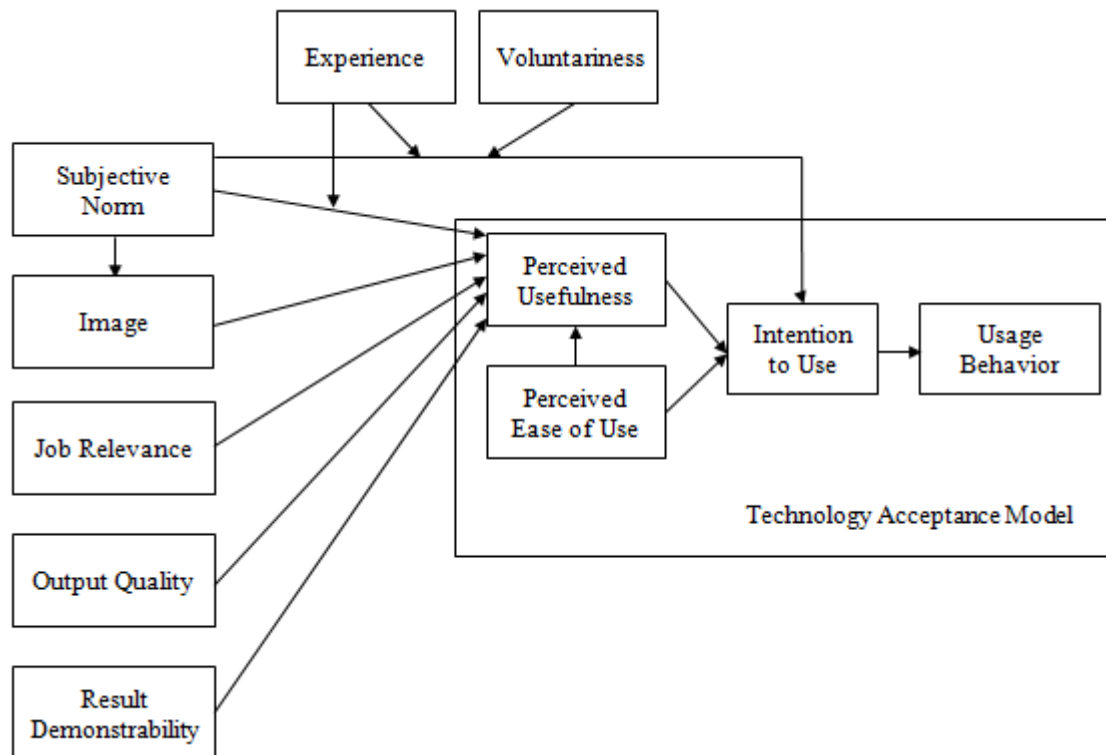
Figure 4. Technology Acceptance Model 2 (Venkatesh & Davis, 2000)

Schepers and Wetzels (2007) tested a conceptual model related to TAM2 via meta analysis ($k = 63$) that included subjective norms, one of the antecedents of perceived usefulness in TAM2, as an antecedent of both perceived usefulness and behavioral intention. However, this conceptual model also included the 'attitude toward use' construct dropped by TAM2. Schepers and Wetzels (2007) model explained 48% of the variance in behavioral intention and 30% of the variance in actual system use. It should be noted that of the 63 studies included, only nine tested the relationship between behavioral intention and behavior, further demonstrating the greater emphasis on predicting behavioral intention (i.e., acceptance) rather than use. The range of correlations between behavioral intention and behavior across these nine studies varied greatly (.25 to .70) and was highly heterogeneous, suggesting substantial population

variability in the relationship. Thus, moderators of this relationship are likely, a finding supported by the findings of Webb and Sheeran (2006).

Unified Theory of User Acceptance of Technology (UTAUT). UTAUT is a synthesis of TRA, TPB, TAM, TAM2, and other models of behavior and technology acceptance such as the Model of PC Utilization (MPCU) (Thompson, Higgins, & Howell, 1991), Innovation Diffusion Theory (IDT) (Karahanna, Straub, & Chervany, 1999), and Social Cognitive Theory (SCT) (Bandura, 1977, 2001). The impetus for this model was two-fold.

First, Venkatesh et al. (2003) expressed concern over the myriad of models that attempted to explain user acceptance of technology. The number of models typically caused researchers to choose between selecting their own constructs from individual models or choosing one model over an alternative model (Venkatesh et al., 2003). To resolve this issue, Venkatesh et al. (2003) sought to examine the individual components of the most prominent models (listed above) as well as others and highlight those constructs that demonstrated the most theoretical and empirical support for predicting behavior intention in a technology context. The hope was to resolve model differences and provide researchers with a *unified* model that explained the largest amount of variance in behavioral intention.

Second, previous research had demonstrated potential boundary conditions associated with each of the previously discussed models in predicting behavioral intention. Specifically, although each of these models demonstrated relationships between behavioral intention and its most proximal antecedents, it was believed that these relationships might serve as a function of other relevant variables; the relationships

between the antecedents of behavioral intention and behavioral intention were likely

moderated. The moderating variables identified by Venkatesh et al. (2003) were gender,

age, experience with system, and voluntariness. Figure 5 provides the resulting model

from the culmination of work/efforts by Venkatesh and colleagues, which included a

review of prominent models, a comparison of each model's ability to predict behavioral

intention and usage behavior, the formulation of UTAUT, and an empirical validation of

the model.

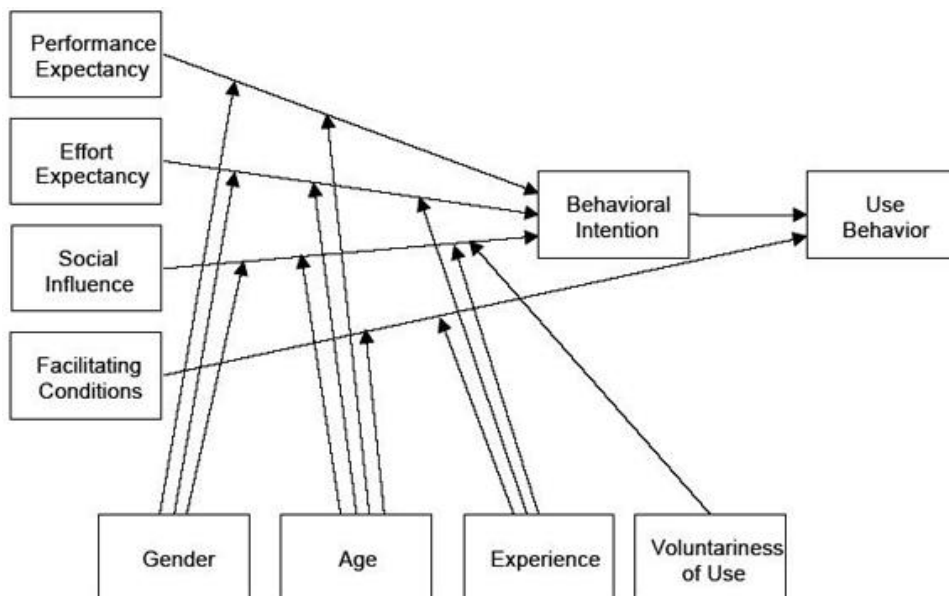*Figure 5.* Unified Theory of Acceptance and Use of Technology (Venkatesh et al.,

2003)

UTAUT did demonstrate an improvement in the prediction of behavioral intention

compared to TAM and TAM2. The addition of additional antecedents explained a great

deal of variance in changes in behavioral intention over time ($R^2 = .70$).   Further, the

authors found that the full model explained approximately 47% of the variance in use

over time. Despite this, UTAUT did not resolve three critical issues also found in TAM and TAM2.

First, the bottleneck issue (see Sniehotta, 2009) persists. UTAUT adds an additional variable to explain variance in use (i.e., facilitating conditions, defined as the extent to which an individual believes that an infrastructure is present to support the use of the technology system), but the focus of the model is still on predicting behavioral intention. Although UTAUT explained approximately 70% of the variance in behavioral intention over time, behavioral intention and facilitating conditions explained only 47% of the variance in actual use. Thus, 53% of variance is system use is unexplained. The continued over-focus on explaining behavioral intention, as opposed to use, by researchers leveraging UTAUT is captured by the meta-analytic results presented by Dwivedi et al. (2011). Specifically, of the 43 studies that use the part or all of the UTAUT model to explain user acceptance, only 8 actually tested the relationship between behavioral intention and use.

Second, the continued absence of a volitional process to explain the mechanistic relationship between behavioral intention and system use is theoretically problematic. Behavioral intention is the likely start of a process that leads to other thoughts, cognitions, and behaviors prior to behavioral engagement. Thus, a volitional component that captures the effect of behavioral intention likely adds to the prediction of use (Brandstätter et al., 2001; Gollwitzer, 1993, 1999; Gollwitzer & Sheeran, 2006; Sniehotta, 2009; Sniehotta, Schwarzer, et al., 2005).

Finally, as with TAM and TAM2, the potential for moderating relationships between behavioral intention and behavior still exists (Legris, Ingham, & Collerette,

2003; Schepers & Wetzels, 2007). The addition of constructs to explain variance in behavioral intention (i.e., performance expectancy, effort expectancy, social influence, and respective moderators of these relationships) does not change the fact that the relationship between behavioral intention and behavior likely function as the result of other relevant variables. The moderator analysis results yielded by Schepers and Wetzels (2007) suggest the presence of moderators between behavioral intention and system use based on a meta-analytic review of TAM.

A Proposed Model

The ultimate purpose of technology acceptance models is to determine what best predicts use. Across TAM, TAM2, and UTAUT, behavioral intention emerged as the best predictor of behavior. As a direct result of the focus on behavioral intention, the prediction of use has improved little over the course of model development, with early models (TAM and TAM2) explaining 36% - 39% of the variance in behavior and UTAUT explaining 41% - 44% (Venkatesh et al., 2003). Thus, a large portion of variance in behavior remains unexplained by UTAUT. Therefore, a current major unresolved issue in technology acceptance research is the lack of theory exploring the causal path between behavioral intention and behavior.

Michie, Johnston, Francis, Hardeman, and Eccles (2008) highlight this lack of theory by presenting several behavioral intervention techniques that affect behavior, but not behavioral intention, including planning, time management, implementation cognitions, discerning prompts, triggers, and cues, and the use of imagery. Further, research has demonstrated that changes in beliefs do not necessarily result in proportionate changes in behavior. In fact, relatively large changes in belief often result

in small behavioral changes (Chatzisarantis & Hagger, 2007; Sniehotta, 2009; Webb & Sheeran, 2006).

These critiques suggest that behavioral intention is not as proximal to behavior as previous work has presumed. Specifically, additional variables that are predicted by behavioral intention likely exist that are *more* proximal to behavior. This study proposed such a mediating framework as well as an individual difference moderator (computer self-efficacy) to better explain the behavioral intention to behavior relationship. Evidence will be presented to support implementation plans as the underlying mechanism of the behavioral intention to behavior relationship.

Further, the role of self-efficacy (specifically, computer self-efficacy) within this model will be investigated. Self-efficacy is defined as an individual's ''judgments of his/her capabilities to *organize* and *execute* courses of action required to attain designated types of performance,'' (Bandura, 1986a, p. 391). Specifically, self-efficacy is one's judgment of their own ability to perform specific task (Bandura, 1977). Further, self-efficacy is considered situation or domain-specific and, subsequently, can vary across contexts (Bandura, 1977). This domain-specific conceptualization allows for the possibility that individuals demonstrate high self-efficacy for one task (e.g., computer use) and not another (e.g., automotive repair). Thus, the proposed model presents a specific form of self-efficacy, computer self-efficacy, as a moderator of the behavioral intention – implementation plan relationship.

Computer self-efficacy is defined as "a judgment of one's capability to use a computer," (Compeau & Higgins, 1995, p. 192). The original conceptualization, test, measurement, and validation of the computer self-efficacy construct was within an

information systems context. The goal of initial research was to identify individual difference variables that predicted usage of computing technology. Compeau and Higgins (1995) sought to supplement TRA (see Fishbein & Ajzen, 1975) in an information systems context with a Social Cognitive Theory (see Bandura, 1986b) perspective. The authors then tested the resulting computer self-efficacy construct in a technology acceptance framework. Their results showed that computer self-efficacy predicted usage directly ($\beta = .23$, $p < .001$) and indirectly via outcome expectancies ($\beta = .24$, $p < .001$), affect ($\beta = .04$, $p < .001$), and anxiety ($\beta = -.50$, $p < .001$).

Although researchers seem to agree on the importance of self-efficacy in predicting behavior (Bandura, 1977; Edwin A Locke & Latham, 2002; Oettingen, Wittchen, & Gollwitzer, 2013), the exact role of this construct in the behavioral intention-implementation plans-behavior framework is not as clear. In an attempt to clarify the role of self-efficacy, this study proposes the construct's consideration as a moderator of both the behavioral intention-implementation plan relationship as well as the implementation plans-behavior relationship. First, evidence will presented to suggest that the relationship between behavioral intention and implementation plans is moderated by computer self-efficacy, such that high self-efficacy individuals are more likely to develop implementation plans following the formation of behavioral intentions compared to low self-efficacy individuals (Latham, Winters, & Locke, 1994; Wood & Bandura, 1989). Research supports the importance of both self-efficacy, behavioral intention, and their interaction in predicting behaviorally related plans such as implementation plans (Gutiérrez-Doña, Lippke, Renner, Kwon, & Schwarzer, 2009; Schwarzer et al., 2010).

Second, evidence will be presented to suggest that self-efficacy also moderates the relationship between implementation plans and behavior. Indeed, previous research supports the moderation of the implementation plans - behavior relationship by self-efficacy (Lippke, Wiedemann, Ziegelmann, Reuter, & Schwarzer, 2009; Wieber, Odenthal, & Gollwitzer, 2010). Specifically, individuals with low-self efficacy are more likely not to act upon their implementation plans due to a lack of task-specific confidence. Conversely, individuals with high self-efficacy are more likely to act upon their implementation plans due to increased confidence in their task-specific ability.

Current research has yet to simultaneously test the potential moderating effect of computer self-efficacy on the behavioral intention – implementation plan relationship and the implementation plan – behavior relationship. Statistical analytic strategies, such as structural equation modeling (SEM), would provide insight on the appropriateness of modeling a simultaneous relationship by allowing for an examination of not only parameter estimates, but also model fit. Further, research that has examined these individual moderating relationships has relied on self-report measures of behavior as well as cross-sectional designs.

Below, I present a discussion of each step of this model (Figure 6) and provide information defining each model component. First, the relationship between behavioral intention and behavior is briefly discussed to allow for the presentation of the hypothesized relationship between these two constructs. This relationship has been discussed in-depth previously and, thus, will only necessitate a cursory review. Second, the relationship between behavioral and implementation plans will be presented. Next, the addition of implementation plans to the behavioral intention to behavior relationship

is discussed, with a focus on theoretical and empirical support for its inclusion into the model. This discussion will also include a review of self-regulation as implementation plans are presented as a strategy indicative of self-regulation (i.e. planning). Next, the inclusion of the individual difference moderating variable, computer self-efficacy, is discussed focusing on the importance of this variables as a moderator of both the behavioral intention to implementation plan and implementation plan to behavior relationship.
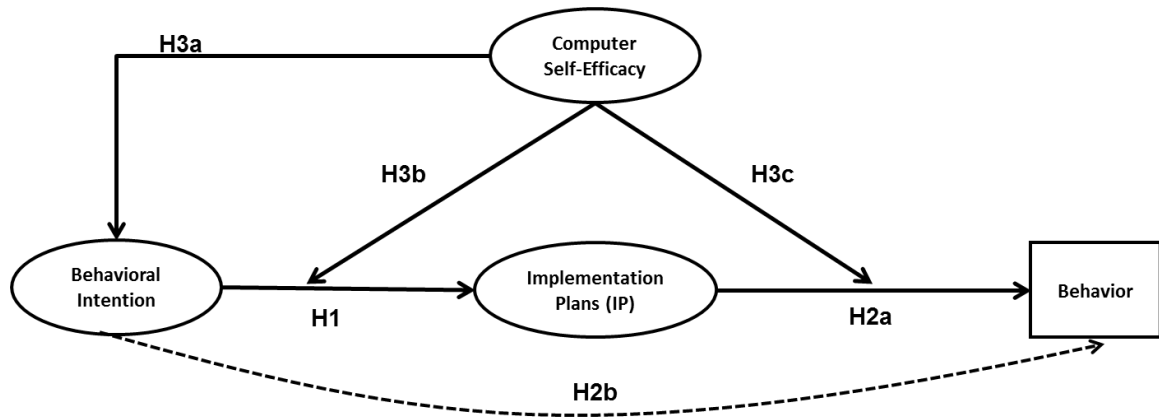
Figure 6. Hypothesized model.

Behavioral intention and behavior. The relationship between behavioral intention and technology use has been well documented (see Davis, 1985; Davis et al. 1989; Venkatesh & Davis, 2000; Venkatesh et al. 2003). This work is grounded in the theoretical work developed by Azjen and Fishbein (see Fishbein, 1975; Azjen, 1985, 1991). The TRA and TBP both specify that behavioral intention, comprised of attitudes related to the behavior in question, represent a motivational assertion regarding likelihood of engaging in a behavior. Technology acceptance models (TAM, TAM2, and UTAUT)

all specify that behavioral intention is the most proximal antecedent of technology use, a relationship supported by empirical tests of each model, respectively.

Behavioral intention and implementation plans. Implementation plans are considered theoretically subordinate to behavioral or goal intentions (Gollwitzer 1993, 1999). Specifically, behavioral intentions reflect a motivational assessment of the likelihood to engage in a behavior, whereas implementation plans reflect the action plans developed to ensure the attainment of the behavioral intentions. Thus, implementation plans are only developed following the development of behavioral intentions (i.e. before plans related to goal attainment are constructed, the goals themselves must first exist). Therefore:

Hypothesis 1. Behavioral intention will predict implementation plans. Specifically, as behavioral intention increases, implementation plans will increase.

Implementation plans as the volitional mediator between behavioral intention and behavior. In a technology acceptance context, behavioral intentions are based on beliefs related to the behavior, such as performance expectancy, effort expectancy, and social influence, as described by TAM (Davis et al., 1989), TAM2 (Venkatesh & Davis, 2000), and UTAUT (Venkatesh et al., 2003). Although a behavioral intention is presumed to predict behavior at another (i.e., future) time point, motivation may decrease over time and constraints inhibiting use can arise (such as time constraints as a result of competing goals), necessitating regulation of cognitions, behaviors, and motivation (Wolters, 2003). Implementation plans represent such a volitional control strategy.

Research supports implementation plans as effective predictors of behaviors (Brandstätter et al., 2001; Gollwitzer, 1993, 1999; Gollwitzer & Brandstätter, 1997; Gollwitzer & Sheeran, 2006; Orbell & Sheeran, 1998; Parks-Stamm et al., 2007; Sheeran, 2002; Sheeran & Silverman, 2003; Sheeran, Webb, & Gollwitzer, 2005b; Webb & Sheeran, 2006, 2008). Goal-setting research provides an explanation as to why implementation plans link behavioral intentions and behavior.

Researchers of goal-setting theory recognize implementation plans as a strategy aimed at aiding self-regulation (Latham & Locke, 2007), the driving force for goal-directed behavior (Kanfer & Ackerman, 1989; Edwin A. Locke & Latham, 1990; Sitzmann & Ely, 2011). Setting a goal establishes a reference point for individuals to strive to attain, and self-regulation is the means by which individuals evaluate, approach, and attain this goal (Locke & Latham, 1990). To attain the goal, individuals must regulate their cognitions and behaviors; in particular, they must devote their effort and attention towards accomplishing the goal and feel confident that goal attainment is possible (Locke & Latham, 1990).

Because implementation plans are plans that are subordinate to behavioral intentions (Gollwitzer, 1993, 1999), the formation of implementation plans represent a manifestation of self-regulation that is likely to benefit the attainment of behavioral intentions. Gollwitzer (1999) specified that the inability to translate goal and behavioral intentions into action is typically the result of failing to get started, becoming distracted, or falling into bad habits, and that setting implementation plans is one approach used to avoid such pitfalls. The regulation of task relevant cognitions (i.e., on-task thoughts), motivation (i.e., self-efficacy) and behaviors (i.e., effort and persistence) are necessary to

ensure that a goal intention is realized/achieved; within a goal setting framework, self-regulation is pivotal. This should also hold true for behavioral intentions within a technology context (i.e., self-regulation translates intentions into behaviors). Self-regulation, in the form of implementation plans, is needed in order to attain behaviors specified by behavioral intentions. Thus, implementation plans likely serve as a strategy, which are subordinate to behavioral intentions and that better explain technology usage behavior.

Although technology acceptance researchers continue the push to further understand the antecedents of behavioral intention, researchers in the behavioral and health psychology arena are well aware of the intention-behavior gap and the possibility of a missing link between intention and behavior (Sniehotta, Scholz, & Schwarzer, 2005). However, throughout this stream of research (Brandstätter et al., 2001; Gollwitzer, 1993, 1999; Gollwitzer & Brandstätter, 1997; Gollwitzer & Sheeran, 2006; Orbell & Sheeran, 1998; Parks-Stamm et al., 2007; Sheeran, 2002; Sheeran & Silverman, 2003; Sheeran et al., 2005b; Webb & Sheeran, 2006, 2008), researchers typically manipulate implementation plan creation instead of considering spontaneous formation of implementation plans as an individual process.

In most cases, an experimental design is used in which participants in an experimental condition are instructed to create implementation plans in conjunction with a goal intention. Then, the prevalence of a target behavior or performance is compared between the experimental and control (no implementation plan manipulation) group. Although instructing participants to form implementation plans and measuring the effect of this intervention on behavior is valuable because it demonstrates the effectiveness of

implementation plans, it does not allow for researchers to fully understand spontaneous implementation plans and the antecedents of the development of these spontaneous implementation plans (e.g., individual differences).

The only exception to this approach is the work of Rise et al. (2003), who created a measure of spontaneously developed implementation plans for recycling and exercising behaviors in order to elucidate the relationships between behavioral intentions, implementation plans, past behavior, perceived behavioral control, and behavior. The researchers found that implementation plans mediated the relationship between behavioral intentions for exercise related behaviors.

Previous experimental research on implementation plans only explains the success of the interventions and does not provide an understanding of the spontaneous development of implementation plans. This spontaneous development and the mechanisms that enable implementation plans to impact behavior (i.e., self-regulation) is the focus of this research. To adequately assess these interrelated relationships, the relationship between implementation plans, self-regulation, and behavior must first be supported. Following this, support must be found for the relationship between behavioral intentions, implementation plans, and behavior. Specifically:

Hypothesis 2a. Implementation plans will predict behavior. Specifically, implementation plans will explain a significant amount of variance in behavior.

Hypothesis 2b. Implementation plans mediate the relationship between behavioral intentions and behavior.

Moderation of the mediational effects by self-efficacy. Meta-analytic results suggest that it is likely that individual differences moderate the relationship between

behavioral intention and behavior (Gollwitzer & Sheeran, 2006; Rhodes, Courneya, & Hayduk, 2002; R. Steel & Ovalle, 1984; Webb & Sheeran, 2006). Because implementation plans are hypothesized to be the mechanism that translates behavioral intentions into behavior, it is likely that this moderation impacts the development of implementation plans. Specifically, if an individual does not possess the appropriate levels of the requisite traits that are expected to impact implementation plans, the formation of behavioral intentions will do little to change behavior. An individual may assert that they have the intention to use a new technology, but may not form intentions around "when" they plan to use the technology, "where" they play to use the technology, and "how" they plan on using the technology; they may not form implementation plans.

Because implementation plans are a type of self-regulatory strategy, a review of self-regulation work further informs this relationship. Individuals vary in their ability to engage in activities/strategies aimed at aiding self-regulation (Boekaerts et al., 2000; Paul R. Pintrich, 2000; P. R. Pintrich, 2004). Specifically, individuals are not equally effective at developing in self-regulatory strategies following the formation of a goal intention. If implementation plans (a hypothesized self-regulation strategy) are the mechanism that engenders the realization of behavioral intentions, the ability to form implementation plans likely yields inter-individual variance. This individual difference possibly explains why changes in behavioral intention do not reflect proportionate changes in behavior (Scholz, Nagy, Göhner, Luszczynska, & Kliegel, 2009; Sniehotta, 2009). Specifically, although individuals may form a behavioral intention, the likelihood of the behavioral intention leading to implementation plan (and subsequent behavior) is contingent on the level of relevant individual difference variables.

A review of goal-setting (Locke & Latham, 2002), social-cognitive (Bandura, 1977), and temporal motivation theory (Steel, 2007) points to self-efficacy as a possible moderator of the relationship between behavioral and implementation plans. With regards to behavior, self-efficacy is theoretically relevant due to the construct's relationship task engagement as well task effort (Bandura, 1989, 1995; Orvis, Orvis, Belanich, & Mullin, 2007). Research has shown that high self-efficacy individuals are more likely than those with low self-efficacy to develop effective task strategies (Latham, Winters, & Locke, 1994; Wood & Bandura, 1989). Specifically, self-efficacy influences an individual's choice regarding goal-directed plans or strategies (Bandura, 1989; Maddux & Volkmann, 2010). Social-cognitive theory specifies that this is due to the fact that individuals are more likely to implement plans that they believe can be executed. Additionally, temporal motivation theory specifies that individuals are less likely to engage in procrastination when they possess a high-level of self-efficacy (Steel, 2007). Further, self-efficacy is well known as a common moderator of the goal – performance relationship (Locke & Latham, 2002).

As stated by Sniehotta, Scholz, et al. (2005), "Once a behavioural intention to engage in regular exercise is formed, the motivation phase is completed and the person enters the volitional phase. The intended behavior must be planned, initiated, maintained and restarted when setbacks occur," (p. 146). Thus, although computer self-efficacy may predict initial motivations to use a computer technology (i.e., behavioral intention), it likely is also relevant for the planning, or volitional, phase of technology behavior; "self-efficacy determines, among others, the effort spent initiating and maintaining behavior," (Sniehotta, Scholz, et al., 2005, p. 146). Sniehotta, Scholz, et al. (2005) found that

maintenance self-efficacy, a judgment of one's ability to maintain a newly adopted behavior, predicted planning (which was considered analogous to implementation plans). Further, planning mediated the relationship between behavioral intentions and behavior (i.e., exercise).

Although Sniehotta, Scholz, et al. (2005) did not model maintenance self-efficacy as a moderator of the behavioral intention – planning relationship, it is likely that the relationship between behavioral intentions and implementation plans does vary as a function of self-efficacy (i.e., computer self-efficacy for this current effort). The absence of this interaction implies that those with high levels of computer self-efficacy are likely to accept any computer technology, regardless of behavioral intention (which is comprised of judgments regarding usefulness of, as well as expected effort to use, the technology).

However, another explanation is that individuals form behavioral intentions regarding the use of a computer technology based on the aforementioned beliefs (i.e. those discussed in TAM, TAM2, and UTAUT). Then, those with strong behavioral intentions and high levels of computer self-efficacy (compared to those with low computer self-efficacy) are likely to form implementation plans (i.e., the *how, when, where* plans), a hypothesized key mechanism for the effect of behavioral intention on technology acceptance. This relationship has been supported by prior research. Using a sample 1718 participants, Schwarzer et al. (2010) found that that those with higher behavioral intentions and higher self-efficacy were more likely to form plans regarding dietary behavior. The effects of behavioral intention, self-efficacy, and their interaction term accounted for 18% of the variance in planning. Gutiérrez-Doña et al. (2009) also

found a significant interaction between behavioral intention and self-efficacy in predicting planning. The effects of behavioral intention, self-efficacy, and their interaction term also accounted for 18% of the variance in planning. Although social-cognitive theory (Bandura, 1977), as well as prior technology acceptance research, specifies that self-efficacy impacts the goal/behavioral intentions individuals adopt or attempt to pursue, it is also likely that self-efficacy moderates the relationship between behavioral intention and the development of implementation plans. Thus:

Hypothesis 3a. Computer self-efficacy is related to behavioral intention. Specifically, those individuals who possess higher levels of computer self-efficacy are more likely to form behavioral intentions related to use.

Hypothesis 3b. The relationship between behavioral intentions and implementation plans varies as a function of computer self-efficacy, such that those who express a behavioral intention to engage in a behavior (i.e., technology acceptance) that are high in computer self-efficacy are more likely to form an implementation plan than those low in computer self-efficacy.

In addition to the moderating relationship of behavioral intention and computer self-efficacy to predict implementation plans, it is also likely that self-efficacy plays a role in translating implementation plans into behaviors. Bandura (1977) suggests that self-efficacy plays an important role in impacting goal-attainment, behavior, and performance due to the fact that highly efficacious individuals are more confident in their ability and, thus, are more likely to remain committed to attaining a goal and/or achieving an intended level of performance. Conversely, individuals low in self-efficacy are less likely to persist in the face of adversity (e.g., conflicting goals, task-difficulty, limited

resources) due to self-doubt and lack of confidence in their ability to perform at a desired level (Bandura, 1977). Bandura's (1977) theoretical assertions are supported by research that has demonstrated that self-efficacy is positively linked to subsequent performance (Colquitt, LePine, & Noe, 2000; Gist, Schwoerer, & Rosen, 1989; Kozlowski et al., 2001; Martocchio & Judge, 1997; Phillips & Gully, 1997) and improves goal attainment across a variety of tasks (see Bandura, 1997; Judge, Jackson, Shaw, Scott, & Rich, 2007; Stajkovic & Luthans, 1998).

In addition to a direct relationship with behavior and goal attainment, research also supports a moderating effect of self-efficacy in the implementation plans – behavior relationship. Here, researchers suggest that implementation plans are most effective when supplemented by high self-efficacy beliefs (Lippke et al., 2009; Oettingen et al., 2013; Wieber et al., 2010). Wieber et al. (2010) manipulated both implementation plans and self-efficacy beliefs to determine if individuals who received an intervention directing them to form implementation plans in addition to receiving an intervention intended to boost their self-efficacy would perform higher on an analytic reasoning test. The results showed that individuals who received both the combined implementation plan and self-efficacy intervention scored higher on the more difficult of the analytic reasoning items.

Although the manipulation of both constructs simultaneously leaves the precise mechanism unclear, research by Lippke et al. (2009) lends support to a moderating role. In their study, Lippke et al. (2009) tested the moderating role of self-efficacy in the relationship between plans, a construct similar to implementation plans, and health behaviors. Additionally, this relationship was tested as part of a larger moderated

mediation, theorizing plans to mediate the relationship between behavioral intentions and health behaviors. Further, Lippke et al. (2009) did not manipulate plans (i.e., the development of plans were not proposed to participants as a viable strategy for attaining health behavioral goals) or self-efficacy. Lippke et al. (2009) found that 1) plans partially mediated the relationship between behavioral intentions and self-reported health behaviors and 2) self-efficacy moderated the plans – behavior relationship.

In line with the aforementioned literature and research findings, it is hypothesized that:

Hypothesis 3c. The relationship between implementation plans and behavior varies as a function of computer self-efficacy, such that those who have developed more implementation plans that are high in computer self-efficacy are more likely to demonstrate higher use than those low in computer self-efficacy.

CHAPTER II

METHOD

Participants

The total of 453 participants participated in the study. The sample consisted of

employees from an international consulting agency headquartered in the eastern United

States. The sample was chosen in order to assess the validity of the model within an

actual work setting with employees that are given the discretion of whether or not to use

an actual end-user program, increasing the external validity of the model to such settings.

The organization is comprised of multiple operating groups based on sector (e.g. an

Energy Consulting group within an Environmental sector). For this research, all

participants were members of one of these operating groups.

Participants were recruited via email invitation from a senior executive within

each operating group. Solicited participants were informed that participation was

completely voluntary, non-billable, and unrelated to performance assessment.

Individuals who participated in the study were eligible to receive a gift card with three

denominations ($100, $50, and $25) based on a random drawing following the

completion of data collection. All Internal Review Board (IRB) ethical guidelines were

followed to ensure the protection and ethical treatment of participants.

The sample demographics revealed a relatively diverse group of participants and

are reported for the 406 participants remaining after various data cleaning tasks. The

sample consisted of 166 (41%) male and 240 (59%) female full time employees. The

sample was approximately 68% White/Caucasian, 13% Asian, 7% Black/African

American, and 11% either Hispanic or Latino, American Indian or Alaska Native, Native

Hawaiian or Pacific Island, or other. The average participant was 39.24 years old (SD =

10.72), with an average company tenure of 6.75 years (SD = 6.03).

Although various rules of thumb exist for determining the appropriate number of

participants to test an effect for Structural Equation Modeling (for a review, see

Westland, 2010), various analyses were conducted to determine the number of

participants needed 1) to obtain satisfactory values for various model fit indices

prescribed by Kim (2005) and 2) detect a change in R^2 for the hypothesized moderated

relationship. For each power analysis, a desired power of .80 and a significance level of

.05 were used as suggested by Kim (2005). Further, degrees of freedom for these fit

indices was equal to 248 (based on 24 observed variables and 52 parameters). A website

created by Timo Gnambs was used to generate the SPSS syntax used to calculate the

required sample size (Gnambs, n.d.). The result of this power analysis revealed that

approximately 389 participants were needed to test the hypothesized model. Based on

the current sample size, there was sufficient power a priori to test study hypotheses at

predicted effect sizes.

Materials

To test the hypothesized model, participant use of Microsoft Lync was analyzed.

Throughout their work day, employees may choose to use Lync to engage in simple text-

based messaging with other employees, phone or video conference employees that are

either onsite or working remotely, engage in text-based, audio or video group

conversations, host audio or full video/audio meetings, share desktop screens, present

content using the Lync whiteboard, and share user files. Lync is deployed across the

organization. Further, at the time of this study the organization specified that Lync was

the organizationally supported communication software. All employees in the participant

pool had access to Microsoft Lync. Screenshots of the software are provided in Figure 7.

Figure 7. The Microsoft Lync software

Procedure

Participants were first asked to view a notification document (see Appendix A)

that outlined the purpose of the study as well as the use of their Lync data. Next,

participants completed a background information questionnaire that included basic

demographic information (e.g. age, gender, race, organization tenure, position title,

employee ID) items (see Appendix B). Participants then completed the behavioral

intention, computer self-efficacy, and implementation plan measures (discussed in depth

below; Appendices C-E respectively). All data were collected electronically via a survey

software package. Finally, participants were be debriefed on the purpose of the study

(see Appendix F).

In order to support causality, a time lag between the collection of behavioral

intention and behavior (i.e. Lync use) was used. The current behavioral intention

literature does not specify an ideal time-frame for measuring behavior following the

measurement of behavioral intention. Meta-analytic research demonstrates that

prolonged time intervals between the measure of behavioral intention and behavior can

attenuate the relationship between the constructs (Sheeran & Orbell, 1998). For this

meta-analysis, Sheeran and Orbell found that the average correlation for "short intervals"

(10 weeks or less, the median time interval) was $r = 59$. Alternatively, for periods longer

than 10 weeks, the correlation significantly decreased, $r = .33$. This attenuation was also

suggested by both Ajzen (1985) and Ajzen and Fishbien (1980). However, these authors

merely stated stronger relationships would be obtained from shorter relationships. Thus,

a time lag of one month was pursued for this study; a one month time lag relative to the

completion of the survey for each individual participant was used to dictate the start date

for the measurement of Lync use. During this time, an organizational member

unaffiliated with the project ran a query on Lync data for participants within the operating

group in question. Linkages between survey data and Lync data were made via the use of the employee ID.

Measures

Descriptions of all measures are provided below. Further, all measures can be found in Appendices C - E.

Behavioral intention. Behavioral intention to use the Lync software was measured using an adaptation of a three-item behavioral intention measure developed by Venkatesh et al. (2003). The adaption of this measure is the reference point in the item stem. Original scale items referenced a "system," whereas the measure for this study referenced Lync. The adapted items were "I intend to use Lync within the next month," "I predict I would use Lync in the next month," and "I plan to use Lync in the next month." Possible responses range from 1 (*strongly disagree*) to 5 (*strongly agree*). The scale yielded a Cronbach's α = .99 (M = 4.51, SD = .93). These items can be found in Appendix C.

Implementation plans. Previous research only provides two measures of spontaneously created implementation plans. Rise et al. (2003) measured implementation plans by asking participants whether or not they had made detailed plans about when, where, what, and how the intend to perform a specific activity (i.e., exercise) in the future. Examples of items include, "I have made plans where I am going to do the exercise," and "I have made plans what kinds of exercise actions to be involved in." Participants responded with a "yes" or "no" response, with "yes" responses scored as a two (2) and "no" responses scored as a (1). Final scores were summed to yield a final implementation plan score, ranging from a possible four (4) to eight (8) points.

However, research suggests that such a measurement scale (i.e. dichotomous) is not optimal. Jones (1968) demonstrated that participants expressed a preference for multiple-response scales (i.e. three or more) over dichotomous scales. Further, Preston and Coleman (2000) demonstrated that test-retest reliabilities as well as internal consistency (Cronbach's alpha) were the lowest for dichotomous scales. Two-point scales (along with three and four point scales) demonstrated the lowest criterion related validity (i.e. criterion correlations), although the differences between scales were not statistically significant. Differences in item-whole correlations between the two-point scales and all other scales were statistically significant, with the two-point scales yielding the lowest coefficient (Preston & Coleman, & 2000).

Brickell and Chatzisarantis (2007) measured implementation plans using a five item measure with a seven-point Likert-type scale. This scale assessed whether or not participants had made plans regarding future exercise behavior. Example items include, "I have planned when I am going to exercise," "I have planned how I am going to exercise", and "I have committed myself to a certain time to exercise." Possible responses ranged from 1 (*not at all*) to 7 *(very much)*.

The current study combined both of the aforementioned measures, adapted the frame of reference of the items (i.e. Lync), changed the physical references (i.e. "where") to functional references (i.e. "which), and modified the response scale to create a final implementation plans measure. The adapted items solicited information regarding the frequency of plans a respondent has for various situations. As an example, the original item "I have planned where I am going to exercise," was adapted to "In the next month, I have a plan for […] type(s) of tasks where I'm going to use Lync," with possible response

options including *zero*, *a few*, *many*, and *every*. Additional items was added to assess

commitment not only to situations, but also commitment to activities. The adapted scale

contained nine items and was assessed using a four-point Likert scale, with responses

ranging from 1 (*Zero*) to 4 (*Every*). The measure yielded a Cronbach's α = .97 (M =

2.41, SD = 0.75). These items can be found in Appendix D.

Computer self-efficacy. Computer self-efficacy was assessed using a 10 item

measure developed by Compeau and Higgins (1995). This measure asked respondents to

imagine that they were given a new software package for some aspect of their work and

then respond to the items within the measure. The computer self-efficacy measure is not

software specific because it measures general self-efficacy across computer software

applications. Example items included, "I could complete the job using the software if

there was no one around to tell me what to do as I go," and "I could complete the job

using the software if I had never used a software package like it before."

The Compeau and Higgins (1995) measure instructed asked participants to

indicate whether they agreed (*yes* or *no*) with the item statements and, for "yes"

responses, indicate their confidence in their response, ranging from 1 *(not at all*

confident) to 10 (*totally confident*). As discussed above, the use of dichotomous (i.e. yes

vs. no) response scales is not optimal. Thus, the current study adapted this measure to fit

a 5-point scale of agreement, with possible responses ranging from 1 (*strongly disagree*)

to 5 (*strongly agree*). This measure yielded Cronbach's α = .87 (M = 3.89, SD = 0.62).

These items can be found in Appendix E.

Behavior (Lync usage). Behavior was operationalized as Lync usage, because

Lync is the focus of the behavioral intention, implementation plans, and self-regulation

measures. Usage was measured as the number of times (count) that a participant initiates the use of Lync's: 1) instant messaging, 2) conference, and 3) audio capabilities over a one month period. These counts were be summed and aggregated by user to arrive at a final measure of use.

The measure focused on the initiating user as the Lync database does not capture whether or not the recipient of the interaction used the Lync system in response. As an example, a user could send an individual an instant message, but based on the available data, it is unclear whether or not the recipient ever responded. Although conversation length could have potentially been queried to discern number of total text characters or number of exchanges with an instant message conversation, there is no comparable information available for conferences and audio.

Further, although duration was captured by the Lync server, this metric was not optimal for two reasons. First, the duration of an instant message conversation captures the time the initiating user allows the instant messaging window to remain open, as opposed to the actual duration of the conversation. Thus, if a user initiated an instant message conversation at 8am and then closed the conversation window at 5pm, the duration metric would have yielded a time of nine hours (regardless of the true length or extent of the conversation) and therefore introduce a great deal of measurement error. Secondly, duration of audio calls could potentially include periods where an initiating user is on hold, thus confounding the operationalization of use by duration. Therefore, the operationalization of use was the frequency of use, as this measure captures the specification of behavior that is of interest to this research (i.e., use of technology).

Over a one month period, Lync was used an average of 72.33 times, which equates to approximately three uses per calendar workday (i.e., Monday – Friday). However, interpretation of this mean value is limited given the positively skewed distribution of the behavioral data. It should be noted that this distribution was expected, with approximately 12% of the participants not using Lync at all across the one month period.

CHAPTER III

RESULTS

Data Cleaning and Descriptive Statistics

Prior to analyzing the survey and Lync behavioral data, data were inspected for

abnormalities and assumption violations and were adjusted or removed when appropriate.

These procedures are discussed below. First, subjects missing a substantial portion of

survey data that hindered the calculation of a mean score for any study variable (i.e.,

behavioral intentions, implementation plans, or computer self-efficacy) were reviewed.

Surprisingly, the majority of participants (n=449; approximately 99% of respondents)

responded to all study variable items. However, three participants failed to answer any

items on at least one of the study variables of interest. These participants were removed

from subsequent analyses.

When developing the electronic survey, participants received an open link to

access the survey content (as opposed to a unique survey link). Thus, it was possible for

participants to access and take the survey more than once. To ensure that the dataset did

not contain duplicate data, the final dataset was inspected for the presence of outliers, as

evidenced by duplicate employee ID numbers. After reviewing the dataset, two

participants were found to have taken the survey twice. To avoid introducing threats to

internal validity (i.e., testing effects, see Shadish, Cook, & Campbell, 2002) and to ensure

independence of observations, the second accession for these two participants was

removed.

The data were next reviewed to ensure that all participants had access to the Lync

software. As Lync usage was the outcome variable of interest, including a participant

who did not have access to the Lync software (e.g., an employee who works on a client

site and is not permitted to use communication software) would not be appropriate. A

total of 35 participants stated they did not have Lync installed on their computer. Thus,

35 unique participants were excluded from the final dataset due to the fact that they did

not have the Lync software on their computer. Descriptive statistics of all observed

variables at this stage of the data cleaning process appear in Table 1.

Table 1
Descriptive Statistics of Observed Study Variable

Variable	*M*	*SD*	Skew	Kurtosis	1	2	3
1. BI[1]	4.50	0.94	-2.18	4.44	--		
2. CSE	3.89	0.63	-0.28	0.45	.13**	--	
3. IP	2.41	0.75	0.09	-0.45	.36***	.18***	--
4. Lync Usage	71.93	80.07	1.83	4.80	.22***	.13*	.41***

Note. $N = 415$. BI = Behavioral Intention, CSE = Computer Self-Efficacy, IP =
Implementation Plans.
[1] Inverse transformation of reflected mean
***$p < .001$, **$p < .01$, *$p < .05$

An investigation of skew and kurtosis of study variables, as well as item

intercorrelations, led to some unexpected findings. First, the behavioral intention

variable demonstrated a substantial negative skew and a high mean as shown in Table 1.

Items were also intercorrelated extremely highly (between r = .98 and r = 1.00). Because

this level of skew did not meet the distributional assumptions of the maximum likelihood

estimator (necessary to test hypothesized latent interactions) and because the

intercorrelation pattern would cause convergence issues, a unit-weighted composite of

behavioral intention was calculated and then transformed via square root, natural log, and

inverse transformations (using a reflected mean value). Skew and kurtosis were the most

acceptable for the inverse transformation of behavioral intention, so this inverse became

the working indicator for behavioral intention. Thus, behavioral intention was not treated as latent in hypothesis testing. The implications of this will be described later, as a limitation to this study.

Data were next inspected in order to detect insufficient effort responding. Huang, Curran, Keeney, Poposki, and DeShon (2012) discuss how insufficient effort responding can be problematic for survey research and provide suggestions for investigating such response patterns. Meade and Craig (2012) demonstrated that inspecting Mahalanobis Distance values for scale items is a valuable post-hoc insufficient effort response detection strategy as these values were significantly negatively correlated to self-reported diligence ($r = -.24$), attitude ($r = -.29$), and effort ($r = -.27$) of survey respondents as well as total time spent on survey ($r = -.23$) and bogus item fail rate ($r = .39$). Three Mahalanobis Distance values were created (one per study scale), normed within scale, and then averaged, per Meade and Craig's recommendations. The distribution of this normed average was then examined for extreme outliers (values that are three interquartile ranges beyond the inner fence in a box and whisker plot), signifying problematic responses across study scales. This analysis resulted in the removal of seven participants.

Finally, transformed data were inspected for the presence of univariate and multivariate outliers. No extreme univariate outliers (values that are three interquartile ranges beyond the inner fence in a box and whisker plot) existed for variables expected to be normally distributed: computer self-efficacy, and implementation plans. When inspecting multivariate outliers, Mahalanobis Distance values were calculated and reviewed for the behavioral intention, computer self-efficacy, and implementation plans

variable. This analysis resulted in the removal of two participants. Thus, after data

cleaning, a total of 406 participants remained (approximately 89% of respondents).

These participants were used for subsequent analyses and for hypothesis testing.

Measurement Models

Prior to testing the structural models and study hypotheses, individual latent factor

structures as well as a full measurement model were assessed. Latent factor structures

were investigated individually to provide evidence supporting construct validity and to

ensure that any later misfit or nonconvergence would not be the result of poor univariate

fit or nonconvergence. Analysis of the complete measurement model was next conducted

to ensure that, prior to hypothesis testing, a model containing all latent factors and

observed variables converged and yielded adequate fit. All models were assessed via

structural equation modeling (SEM) using the Mplus 7.2 software with bias corrected

bootstrapping and 1,000 replications, as recommended by Preacher and Hayes (2008).

Overall model fit was examined using multiple global fit indices, as recommended by Hu

and Bentler (1999). Latent factor structure and measurement model fit statistics (where

available) can be found in Table 2.

Issues of poor fit (see Table 2) arose when testing the latent factor structure of

computer self-efficacy. This was surprising, as prior literature (see Compeau & Higgins,

1995) has shown high factor loadings for the items on the computer self-efficacy factor.

Because the latent factor structure was not the focus of this study, modification indices

displayed in the model output were displayed. Modification indices specify error terms

that, if correlated, will reduce the overall Chi-square statistic by a value of at least 10 and,

thus, improve model fit. By allowing seven of these error terms to correlate, model fit

was improved to acceptable values (see Table 2). Thus, because a) the goals of this research were to test a measurement and structural model to assess the relationships among latent factors and behavior, b) prior research has supported the content validity and factor structure of the computer self-efficacy scale, and c) the relationship between the computer self-efficacy items is not the focus of this research, a composite CSE mean score was used to assess the subsequent models.

Initially, the nine-item implementation plan factor demonstrated poor fit (see Table 2). Upon inspection of the Mplus output, modification indices suggested correlating the error terms for two scale items. A review of these items demonstrated that they were unique from the other seven insomuch that they asked participants to express how many activities/situations in which they had committed to using Lync. Further, modeling the correlation seemed acceptable because the main difference between the items was the phrase activities vs. situations. A subsequent model assessed with the correlated path modeled. This adjusted nine-item implementation plans factor demonstrated acceptable fit, (see Table 2). Further, all factor loadings yielded statistically significant parameter estimates, with standardized estimates ranging from .83 to .92.

When initially attempting to assess the fit statistics for the complete measurement model (including: a) the inverse transformed reflected mean indicator behavioral intention factor, b) the composite computer self-efficacy factor, c) the 9-item implementation plans latent factor, and d) the observed Lync usage factor as a count variable with a zero-inflated Poisson distribution), the model would not converge. Upon inspection, large values for the Lync usage factor were flagged by Mplus as potentially

problematic, and the Mplus output suggested considering the count variable to be a continuous variable. Thus, Lync usage was transformed using a square root transformation. This transformation yielded acceptable skew (0.36) and kurtosis (-0.39) statistics. Updated survey variable means, standard deviations, and correlations are provided in Table 3 below, including the mean of the composite computer self-efficacy variable as well as the mean transformation of both behavioral intention and Lync usage.

Table 2
Model Fit Statistics for Latent Factor and Measurement Models

Model	χ^2	df	p	AIC	CFI	RMSEA	SRMR
CSE	631.68	35	.00	9187.53	.72	.21	.12
CSE_{MI}	140.88	28	.00	8710.78	.95	.10	.06
IP	272.193	27	.00	5194.28	.94	.15	.02
$IP_{8\cdot9}$	54.58	26	.00	4978.57	.99	.05	.01
MM	100.36	50	.00	8045.94	.99	.05	.02

Note. N = 406. CSE = Computer Self-Efficacy, CSE_{MI} = CSE with freed covariances between error terms using modification indicies, IP = Implementation Plans, $IP_{8\cdot9}$ = Implementation Plans with items 8 and 9 correlated, MM = Measurement Model.

Table 3
Descriptive Statistics of Final Study Variables

Variable	M	SD	Skew	Kurtosis	1	2	3
1. BI	.83	.28	-1.11	-0.53	--		
2. CSE	3.89	0.62	-0.18	0.10	.22***	--	
3. IP	2.41	0.75	0.08	-0.43	.46***	.20***	--
4. Lync Usage	7.03	4.79	0.36	-0.39	.38***	.13**	.47***

Note. *N* = 406. BI = Behavioral Intention, CSE = Computer Self-Efficacy, IP = Implementation Plans.
***$p < .001$, **$p < .01$, *$p < .05$

The final complete measurement model included the behavioral intentions composite indicator, the composite computer self-efficacy factor, the latent implementation plans factor, and the observed Lync usage indicator with all items

modeled as correlated (see Figure 8). This model demonstrated acceptable fit (see Table 2).
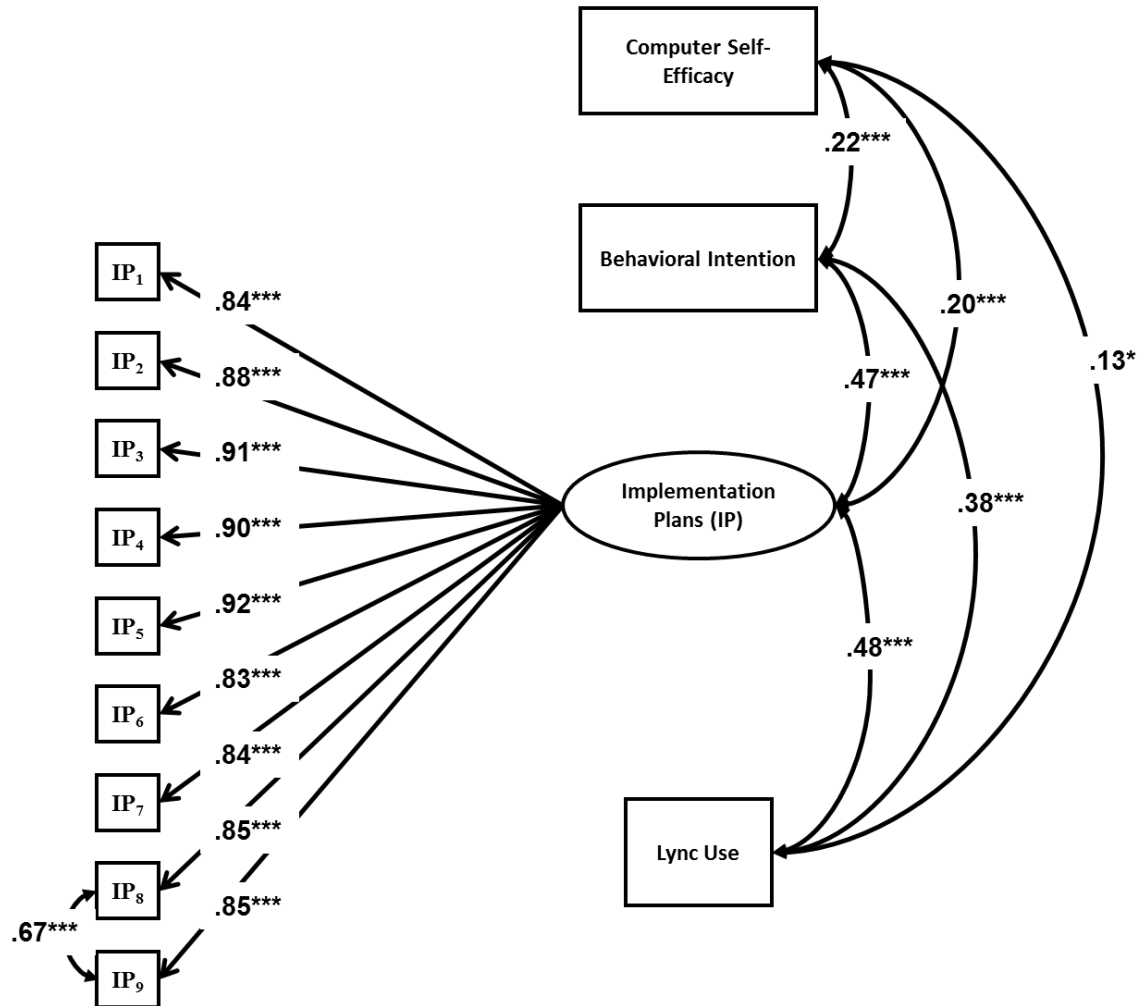
***$p < .001$, **$p < .01$, *$p < .05$

Figure 8. Final Measurement Model with Standardized Factor Loadings

Structural Models

After developing a fitting measurement model, the next step was to examine the relationships among the latent factors and assess the structural model. In order to ensure that the parameter estimates used to test study hypotheses were yielded from a model

with adequate fit, two structural models were tested: 1) a model containing all hypothesized latent factors and effects except latent interactions and related paths (the restricted model) and 2) a model containing all hypothesized factors and effects (the complete model). These models were differentiated partially due to a limitation of Mplus; when latent interaction terms are modeled, classic fit statistics cannot be calculated. Thus, model fit can be assessed with CFI, RMSEA, and SRMR in the restricted model, but not the complete model. Instead, model comparisons were conducted by comparing the Akaike information criterion (AIC) and Bayes information criterion (BIC), as these fit statistics can be used to assess nested or non-nested models (Schumacker & Lomax, 2004). Specifically, if the restricted model was more likely the better fitting model, it would have served as the source of parameter estimates for hypothesis tests. If the complete model was more likely to be better fitting, it would have served as the source instead.

The restricted model contained all study factors as well as the hypothesized relationships among factors, excluding the hypothesized moderating relationships; this model tested Hypotheses 1 − 3a (see Figure 9). The complete model tested the full hypothesized model shown in Figure 9; all hypothesized indirect, direct, and interaction paths were modeled; this model enabled the assessment of Hypotheses 3b and 3c.
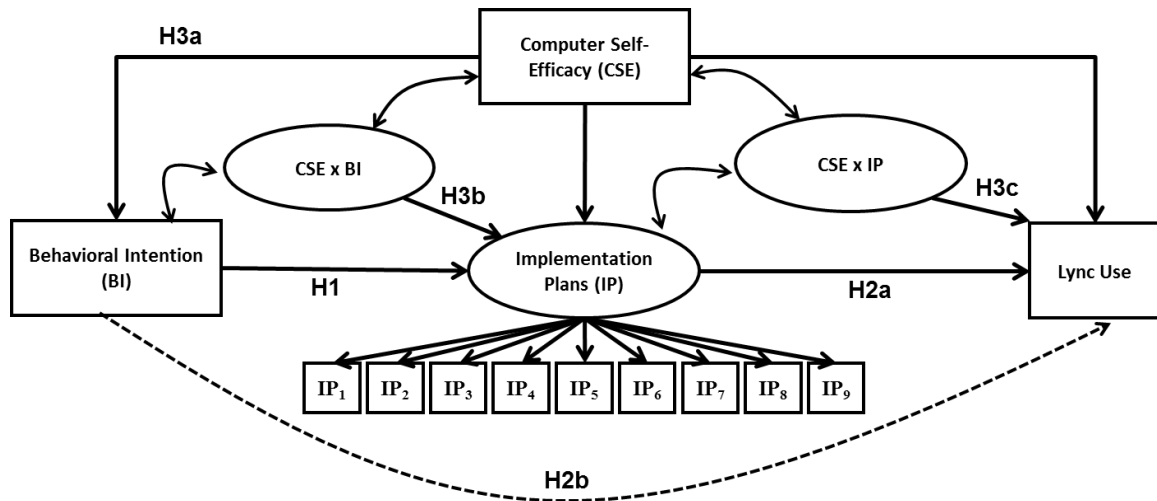
***p* < .001, ***p* < .01,

Figure 9 Hypothesized Complete Structural Model

Both models were assessed via structural equation modeling (SEM) using the

Mplus 7.2 software with EM imputation. Bootstrapped parameter estimates and

traditional fit statistics are not available when testing latent factor interactions.

Therefore, only the restricted model was assessed with bias corrected bootstrapping and

1,000 replications, as recommended by Preacher and Hayes (2008). Model fit statistics

for both the 1) mediation and main effects model and 2) full moderated mediation model

can be found in Table 4.

Table 4
Model Fit Statistics for Restricted and Complete Models

Model	χ^2	*df*	*p*	AIC	BIC	CFI	RMSEA	SRMR
Restricted Model	115.21	51	.000	7292.83	7441.07	.99	.06	.02
Complete Model	NA	NA	-	7294.33	7450.58	-	-	-

A comparison of AIC values between the restricted model and the complete model (ΔAIC = $\text{AIC}_{max} - \text{AIC}_{min =}$ 1.5) suggested that both models are similar with regards to model fit. Burnham and Anderson (2002) state that a ΔAIC < 2 indicates that one model is not necessarily better fitting than another. By calculating AIC weights, where

$$w_i(AIC) = \frac{exp\left\{-\frac{1}{2}\Delta_i(AIC)\right\}}{\sum_{k=1}^{K} exp\left\{-\frac{1}{2}\Delta_i(AIC)\right\}}$$

and the evidence ratio for the model comparison, where

$$Evidence\ Ratio = \frac{w_i(AIC)}{w_j(AIC)}$$

it can be see that the restricted model was 2.11 times more likely to be a better fitting model (see Wagenmakers & Farrell, 2004). Further, an investigation of BIC values provided evidence that suggested that the restricted model was the better fitting model. Nagin (2005) suggests using the following formula

$$b_{ij} = exp\left(BIC_i - BIC_j\right)$$

to determine the relative performance of one non-nested model to another, with values less than 1/10 (or the inverse) suggesting strong evidence for on model over another. Raftery (1995) suggested that twice the raw difference between BIC values, or

$$2 \times \Delta BIC, where \ \Delta BIC = BIC_{max} - BIC_{min}$$

can be used to determine the strength of the evidence for better fit of model versus

another. Calculating both ($b_{ij} < 0$; $2 \times \Delta BIC = 19.02$) the BIC values demonstrated

that the restricted model was preferred. Although the results of the AIC values provided

only partial support for the restricted model, the restricted model was used to interpret

parameter estimates due to the comparison of BIC values and the relative parsimony of

the restricted model. As shown in Table 4, CFI, RMSEA, and SRMR fit statistics for the

restricted model fell within the acceptable ranges prescribed by Hu and Bentler (1999).

Although the Chi-square statistic was significant, the SEM literature suggests that Chi-

square values are overly sensitive to sample size, with larger samples (i.e. > 200) likely to

produce a significant chi-square value despite adequate model fit (Schumacker & Lomax,

2004). Parameter estimates for both the restricted and complete model can be found in

Tables 5 and 6, respectively.

Table 5
Unstandardized Path Coefficients for Lync Usage for Restricted Model

Model	B	S.E.	95% CI
Behavioral Intention			
a. CSE	0.10***	.02	[.06, .13]
Implementation Plans			
a. Behavioral Intentions	1.11***	.13	[.86, 1.38]
b. CSE	0.11*	.05	[.02, .21]
Lync Usage			
a. Implementation Plans	3.36***	.35	[2.65, 4.00]
b. CSE	0.26	.36	[-.47, 0.93]

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

Table 6

Unstandardized Path Coefficients for Lync Usage for the Complete Model

Model	B	S.E.
Behavioral Intention		
a. CSE	0.10***	.02
Implementation Plans		
a. Behavioral Intentions	-0.27	.84
b. CSE	-0.21	.20
c. CSE x Behavioral Intentions	0.37	.22
Lync Usage		
a. Implementation Plans	4.60*	2.10
b. CSE	0.34	.43
c. CSE x Implementation Plans	-0.32	.54

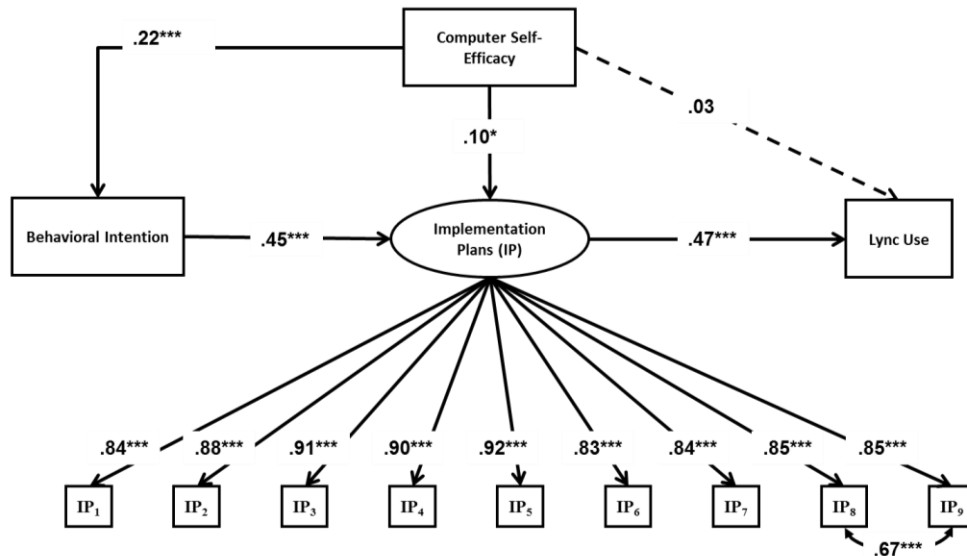Note: Bootstrapped confidence intervals are not available when assessing latent factor moderation in Mplus. CSE = Computer Self-Efficacy
***$p < .001$, **$p < .01$, *$p < .05$.

Hypothesis Tests

The restricted model, along with standardized parameter estimates, is shown in Figure 10.

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

Figure 10. Final Empirical Model with Standardized Factor Loadings

Hypothesis 1 stated that behavioral intentions would be related to implementation plans such that as behavioral intention increases, implementation plans would increase as well. As can be seen in Figure 10 there was a significant, positive direct effect of behavioral intention on implementation plan, $\beta = .45$, $SE = .13$, 95% CI [.86, 1.38]. Thus, Hypothesis 1 was supported.

Hypotheses 2a and 2b proposed a mediating role of implementation plans between the behavioral intention to behavior relationship. Hypothesis 2a stated that implementation plans would predict behavior (Lync usage). As shown in Figure 10, implementation plans related to the use of Lync predicted Lync usage over a one month period, $\beta = .47$, $SE = .35$, 95% CI [2.65, 4.00]. Thus, Hypothesis 2a was supported. Hypothesis 2b stated that implementation plans mediated the relationship between behavioral intention and behavior. In support of Hypothesis 2b, the indirect effect of behavioral intention on behavior via implementation plans (created by multiplying the behavioral intention to implementation plans path by the implementation plans to Lync usage path, see Preacher, Rucker, & Hayes, 2007) was significant, $B = 3.74$, $SE = .57$, 95% CI [2.65, 4.91].

Hypotheses 3a – 3c related to the role of computer self-efficacy in the behavioral intention to behavior relationship. Hypothesis 3a stated computer self-efficacy would predict behavioral intention such that those individuals who possess higher levels of computer self-efficacy are more likely to form behavioral intentions related to use. As shown in Figure 10, computer self-efficacy did predict behavioral intention, $\beta = .22$, $SE = .02$, 95% CI [.06, .13]. Thus, Hypothesis 3a was supported. Hypothesis 3b stated that the relationship between behavioral intentions and implementation plans varies as a function

of computer self-efficacy such that those who express a behavioral intention to engage in a behavior that are high in computer self-efficacy are more likely to form an implementation plans than those low in computer self-efficacy. Hypothesis 3c stated that the relationship between implementation plans and behavior varies as a function of computer self-efficacy such that those who have developed more implementation plans that are high in computer self-efficacy are more likely to demonstrate higher use than those low in computer self-efficacy. Because the BIC values associated with the complete model demonstrated that adding the hypothesized moderated paths resulted in reduced model fit relative to the restricted model, Hypothesis 3b and 3c were not supported.

CHAPTER IV

DISCUSSION

This study had two major goals. The first goal was to empirically test the

hypothesis that implementation plans mediate the effect of behavioral intention on

behavior (Lync usage). A large portion of technology acceptance research has posited

behavioral intention as the most proximal indicator of behavior (Venkatesh & Davis,

1996; Venkatesh & Davis, 2000; Venkatesh et al., 2003). However, because behavioral

intentions are motivational in nature, implementation plans may serve as the volitional

link between behavioral intentions to use technology and actual technology use. This

assertion has not been previously tested within a technology acceptance framework.

Thus, this research is novel in this regard.

The second goal was to identify an individual difference that moderates the

relationships between behavioral intention and behavior.   Variation in effect sizes of the

relationship between behavioral intention and behavior suggested possible moderators

(Webb & Sheeran, 2006). Due to the technological context of the behavior in question,

computer self-efficacy was hypothesized as a moderator of both the behavioral intention

to implementation plans relationship as well as the implementation plans to behavior

relationship. This study demonstrated that the effect of behavioral intention on behavior

occurs indirectly through the development of implementation plans, highlighting the

importance of implementation plans in the realm of technology acceptance and use.

However, the moderating role of computer self-efficacy was not supported.

In addition to demonstrating the mediating role implementation plans, this study

also implemented a novel operationalization of the implementation plans construct.

Previous research (Brandstätter et al., 2001; Gollwitzer, 1993, 1999; Gollwitzer & Brandstätter, 1997; Gollwitzer & Sheeran, 2006; Orbell & Sheeran, 1998; Parks-Stamm et al., 2007; Sheeran, 2002; Sheeran & Silverman, 2003; Sheeran, Webb, & Gollwitzer, 2005a; Webb & Sheeran, 2006, 2008) has typically manipulated implementation plans by requesting that participants create them. In contrast, this study built on a small stream of research (Brickell & Chatzisarantis, 2007; Rise et al., 2003) that conceptualized the development of implementation plans as a process. The value of this conceptualization is that it allows future researchers to investigate additional individual differences that may play a role in the development of implementation plans, as well as contextual factors that may engender or hinder their development.

Another contribution of this study is the use of an objective measure of technology use, operationalized as an initiation of Lync via the chat, conference, and audio capabilities. Previous technology acceptance and use research has relied on self-reported technology usage within a cross-sectional design, leading to measurement concerns. Other objective attempts at measuring technology use have been made, such as number of log-ins, but leave much to be desired regarding fully understanding and predicting actual technology behavior. These operationalizations have been used to determine the amount of variance explained in behavior by behavioral intention and its antecedents. By capturing a more comprehensive measure of behavior, this research perhaps paints a more accurate picture of the amount of variance explained by behavioral intention, implementation plans, and computer self-efficacy. Future research should continue to seek out ways to capture behavior objectively and do so in such a manner so as to capture meaningful variance in the operationalization of the behavioral construct.

Below, these findings are discussed in greater detail, along with the theoretical contributions and practical implications of these findings. Further, study limitations and future research directions are discussed as well.

Theoretical Contributions

The Theory of Reasoned Action (TRA, see Fishbein & Ajzen, 1975) and Theory of Planned Behavior (TPB, see Ajzen, 1985; Ajzen, 1991) are foundational theories of behavior for most of the field of psychology. Other broader psychological theories, such as goal-setting theory (see Edwin A. Locke & Latham, 1990) leverage the theoretical underpinnings of TRA and TPB to posit similar relationships between goal-setting (an intention-like process) and behavior (e.g., goal achievement, performance, etc.). Prior research has consistently showed the relationship between behavioral intention and behavior, but there has been little effort (especially in the technology acceptance realm) to understand intermediate causal processes. Sniehotta (2009) stated that such processes were necessary to translate motivational assertions (i.e. behavioral intentions) into behavior. The results of this study offer support Sniehotta's assertion and suggest that TRA and TPB, as well as models that leverage these theories of behavior, incorporate the role of implementation plans as an intermediary process that enhances the likelihood of behavior.

Although goal-setting and self-regulation research has sought to determine the boundary conditions around the effectiveness of goal-setting, as well as the underlying mechanisms that translate goals into behavior, the majority of technology acceptance research has sought to dive deeper into predicting behavioral intention leaving the relationship between behavioral intention and technology usage relatively unexplored. As

TRA and TPB are foundational for the majority of technology acceptance research, this

finding holds inherit value insomuch that this result was a) based on the foundational

theories that support these technology acceptance models and b) supported within a

technology context. Technology researchers should seek not only to influence behavioral

intention, but the development of implementation plans as well. Gollwitzer (1993, 1999)

discussed how implementation plans are subordinate to behavioral or goal intentions,

such that implementation plans follow the development of behavioral intentions

surrounding the decision of whether or not to engage in a behavior. This research

demonstrated that those individuals who develop more implementation plans regarding

Lync usage were more likely to use Lync. These results are supported by self-regulation

theories (Boekaerts et al., 2005; Karoly, 1993) that suggest that the development of

implementation plans serve as a strategy aimed at aiding the self-regulatory process

necessary to translate intentions into behavior. Thus, implementation plans are indicative

of the initial stages of action, demonstrating that an individual has engaged in a process

aimed at obtaining goals or engaging in a behavior (Gollwitzer, 1993, 1999; Edwin A.

Locke & Latham, 1990). Therefore, these results suggest that behavioral intentions alone

may not be enough to engender actual behavior and implore researchers to focus on the

behavioral intention, implementation plan, behavior process as a whole.

Based on social cognitive theory (Bandura, 1977), an individual's self-efficacy

impacts the goals that an individual pursues and the intentions that an individual forms.

Specifically, individuals with higher levels of self-efficacy are more like to express a

higher level of intention to engage in a specific behavior. The findings of this study shed

light on the importance of computer self-efficacy within a technology acceptance

framework. Within a technology context, computer self-efficacy predicts an individual's behavioral intentions to engage in a technology-relevant behavior. This finding has been supported by prior technology acceptance research as well (Venkatesh et al., 2003). Thus, this study adds to the growing body of evidence that demonstrates the importance of computer self-efficacy for the formation of behavioral intentions. Specifically, lower computer self-efficacy is related to lower behavioral intentions to use an end-user technology. Further, computer self-efficacy also predicted implementation plans even when controlling for behavioral intention. This suggests that individuals with higher computer self-efficacy not only form behavioral intentions, but also are more likely to form implementation plans regarding the behavior. This finding may also be expanded to provide added value to non-technology contexts where other forms of self-efficacy are more relevant, such as exercise self-efficacy (Fletcher & Banasik, 2001), training self-efficacy (Chiaburu & Marinova, 2005), and job-search self-efficacy (Moynihan, Roehling, LePine, & Boswell, 2003). Understanding the role that self-efficacy plays in shaping behavior will help researchers understand how individuals form behavioral intentions and implementation plans to engage in behaviors across many contexts.

Previous research has suggested that the relationship between behavioral intention and behavior may in fact be moderated (Webb & Sheeran, 2006). Research has also suggested that computer self-efficacy may in fact moderate the relationship between behavioral intention and implementation plans (Schwarzer et al., 2010) as well as the relationship between implementation plans and behavior (Lippke et al., 2009; Oettingen et al., 2013; Wieber et al., 2010). However, this study failed to find support for the moderating role of computer self-efficacy for both the behavioral intention to

implementation plans relationship as well as the implementation plans to behavior

relationship. These results may suggest that 1) the effect of computer self-efficacy on the

development of implementation plans is equal regardless of behavioral intention and 2)

the relationship between implementation plans and behavior does not vary based on

computer self-efficacy. However, such a conclusion may be tenuous. Although

composites were used for both behavioral intention and computer self-efficacy, lack of

power to detect both interactions is possible. A larger sample may provide the appropriate

power to detect these interactions.

Overall, the final empirical model (see Figure 10) explained 23% of the variance

in behavior, demonstrating that this study successfully explained a large portion of

variance in behavior. A further investigation of the this model including the direct effect

of behavioral intention on behavior increased the variance explained in behavior by 3%,

for a total of 26% of the variance explained in behavior (CFI = .99, RMSEA = .05,

SRMR = .02). This additional finding highlights the strength of the indirect effect (i.e.

the role of implementation plans), insomuch that this effect explained nearly all of the

direct effect of behavioral intention on behavior. Previous technology acceptance model

research (e.g., TAM, TAM2, UTAUT) has explained in the range of 30% to 47% of the

variance in behavior (Schepers & Wetzels, 2007; Venkatesh et al., 2003). Although a

direct comparison is limited due to the absence of constructs, such as facilitating

conditions (see Venkatesh et al., 2003), there are a few potential explanations for this

difference. First, it should be noted that meta-analytic findings of variance explained in

use are on the low end of this range, with the variance explained in behavior equaling

30% across nine studies (Schepers & Wetzels, 2007). It is possible that the 30% value

represents a more accurate estimate of the variance explained in behavior. Second, a majority of technology acceptance research has relied on participants self-reporting use with a cross-sectional data collection strategy (Straub, Limayem, Karahanna-Evaristo, 1995). Because research has shown a weak correlation between self-report usage and objective measures of use (Straub et al., 1995), such a design could artificially inflate the relationship between study variables (i.e. behavioral intention) and use thus inflating the variance explained in use. Finally, when objective measures of use have been used (i.e., UTAUT, see Venkatesh et al., 2003), they have mostly consisted of very parsimonious operationalizations of behavior, such as number of system log-ins. The current study focused on actual use of the system and over a one-month period. Thus, perhaps the amount of variance explained in behavior for the current study is more accurate due to a criterion that captures behavior more comprehensively.

Additionally, the combined effect of behavioral intentions and computer self-efficacy explained 23% of the variance in implementations plans. These results would suggest that other variables may help to predict the development of the implementation plans. With this finding, researchers should focus on fully understanding the role of implementation plans, such as determining additional antecedents of the construct.

Practical Implications

From an organizational perspective, the results of this study highlight the importance of ensuring that all employees fully understand the purpose and capability of any new organizational technology. Previous research has shown that employees must perceive that the technology has inherent value and that the technology is not overwhelmingly complex before they adopt favorable attitudes surrounding use

(Venkatesh, 1999, 2000; Venkatesh & Davis, 2000; Venkatesh et al., 2003). These attitudes and beliefs are what lead to the development of behavioral intentions (Venkatesh et al., 2003). Although beliefs and attitudes towards a technology play a role in shaping behavioral intentions, ensuring that employees have implementation plans regarding the organizational technology is also important. Specifically, the development of implementation plans help to translate behavioral intentions (which are predicated by attitudes and beliefs) into behaviors. Organizational stakeholders can ensure the development of implementation plans by confirming that employees exhibit the requisite level of understanding to use the technology effectively. This goes beyond simple communication efforts and may necessitate the use of training and hands-on workshops where the capabilities of the technology are made salient to all employees. Such efforts are also likely to bolster an individual's computer-self efficacy because they provide the employee ample time to practice, gain familiarity, and build confidence in their computer ability (Bandura, 1977, 1986a, 1989; Bandura & Cervone, 1983), which would prove advantageous for the development of both behavioral intentions and implementation plans.

Organizations may also seek out or develop technology "champions" (see Lawless & Price, 1992) to assist in the technology implementation process. These employees can help to ensure technology use by disseminating the value and purpose of new technology initiatives to individual employees. Further, technology champions can be tasked with providing clear examples on how the new technology fits into an employee's role, linking the technology and role specific tasks. By providing such

information, technology champions are helping to engender the development of behavioral intentions as well as implementation plans.

Finally, due to the importance of computer self-efficacy throughout the acceptance/use process, it is suggested that organizational leaders remain cognizant of employees' confidence in their own computer ability. Such an understanding would provide insights on how to deploy new technology within an organization. As an example, understanding the general level of employees' computer self-efficacy may help organizational leaders to determine which deployment strategy (i.e. employees as novices, experienced, or experts) would be the most effective.

This study developed a reliable measure of implementation plans that predicted technology usage. Although the frame of reference for this measure was specific to the end-user technology of interest (i.e., Lync), using a similar measure could allow organizations to assess the likelihood employees will use an organizationally supported technology. Employees who express minimal implementation plan development could be targeted for follow-up to determine what is contributing to the lack of implementation plans (e.g. low behavioral intention, minimal computer self-efficacy, or other factors).

Limitations

Although this study has theoretical and practical value, it is not without its limitations. First, due to the high inter-item correlation between behavioral intention items, behavioral intention was measured quite narrowly, preventing empirical testing of it as a latent factor. Additionally, the mean behavioral intention value was higher than expected, suggesting that many participants had strong intentions to use Lync.

Computer self-efficacy also presented a few issues during the data analysis process. Because a) the latent factor structure of the construct was not the focus of the current research and b) the factor structure of the construct has been supported by previous research (Compeau & Higgins, 1995), modification indices were used to allow error terms between indicators of the latent factor to correlate. Thus, for subsequent models, computer self-efficacy was tested as a composite mean score (i.e., an observable factor).

Another potential limitation is the context of the specific technology tool used in the current study. Microsoft Lync is a collaborative communication tool and, thus, antecedents of use for such a collaborative technology may differ from an individual technology (such as a project budget tracking software). Research suggests that, for collaborative technology, factors such as social influence play a larger role in predicting behavioral intentions and use (Cheung & Vogel, 2013; Huang, 2015). Because technology type did not vary, this influence of this characteristic was not testable. However, this distinction provides a valuable future research outlet to determine if behavioral intentions and implementation plans have a differential impact on behavior based on the technology type or, more generally, based on the behavior type (individual vs. collaborative).

Lastly, there were a few limitations regarding the measure of behavior, Lync usage. First, Lync use was transformed using a square root transformation. Any transformation can make the interpretation of coefficients, but such a transformation was needed as a result of high count values. It should be noted that skew and kurtosis values were within acceptable ranges following the transformation. Second, although behavior

captured multiple forms of Lync usage, the current operationalization of Lync usage (a summed count of all instances of Lync) treated all Lync use as equal. Due to limitations regarding the level of detail available for Lync usage, it was also impossible to discern whether an employee who engaged in a phone call actively participated for the full duration. However, it is possible that other operationalizations could have resulted in an even deeper understanding of the hypothesized relationships. As an example, examining word length for text conversations and speaking time for audio conversations may have provided ever more variance in the behavior construct. Future research should capitalize on opportunities to assess these types of behavioral outcomes as opposed to solely relying on count data. Finally, to ensure that Lync use data did not violate the assumption of independence of observations, only initiations of Lync were captured to measure behavior. If all instances of Lync were used (i.e., initiations and reciprocations/responses), observations of use would have been influenced by one another. Although this strategy did ensure that this assumption was not violated, it is possible that certain job titles and/or job roles make the initiation of Lync use more likely. Thus, certain employees may have been more likely to initiate Lync use. Because data was not collected regarding job roles, it is impossible to discern if this would have affected the correlations between study variables. If future researchers wish to measure use in a similar manner to the current study, an assessment of job roles is suggested to investigate this potential confounding factor.

Future Research Directions

In addition to the future research discussed in response to study limitations, other future research opportunities exist as well. First, future research should investigate the

relationships above via a two-part hurdle model (see Cameron & Trivedi, 2013), with stage one predicting who uses versus who does not use technology (i.e., dichotmozing use) and stage two predicting the amount of technology use, similar to the model tested for this research. Such a model would allow for a clearer understanding of users versus non-users. Specifically, a two-stage model would allow for researchers to test for the incidence of use (i.e., a dichotomous variable) as well as the prevalence of use (i.e., the amount of use for individuals who use the technology). It is possible that the strength of the predictors of use vary when investigating incidence vs. prevalence. The small sample size of non-users in the current study did allow for such an examination.

Second, future research should investigate a latent growth model of the relationship between behavioral intention, implementation plans, and behavior over time. Namely, research should follow interventions targeted at increasing either behavioral intention, implementation plans, or both, over more than two time points. Such an intervention may come in the form of training meant to target the development of implementation plans. Baseline behavioral intentions, implementation plans, and behavior could be measured prior to the deployment of the training and then measured again following the intervention. The results from this research would allow for an understanding of how changes in behavioral intentions and implementation plans overtime impact actual behavior. Further, research of this nature would speak to the potential effectiveness of developing training content aimed at increasing the use of organizational end-user technology.

A third stream of research should also investigate personality traits as antecedents of implementation plans. Behavioral intentions and computer self-efficacy together

combined to explain approximately 16% of the variance in implementation plans. Thus, 85% of the variance in implementation plans is unknown. Future research could focus on both individual and organizational antecedents to attempt to explain additional variance. Conscientiousness may play a role in the development of implementation plans due to the nature of the construct. Conscientious individuals are considered to be organized, planful, and achievement-oriented (Costa & McCrae, 1985; Goldberg, 1993). Employees who are organized and planful may be more likely to develop implementation plans to ensure that they follow through on their behavioral intentions. Research in the area of exercise psychology demonstrate how conscientiousness may play a role in the intention-behavior relationship. Conner, Rodgers, and Murray (2007) demonstrated that conscientiousness moderates the intention to behavior (exercise) relationship, but only when the behavior was to be performed in an unusual environment. It is possible that the moderating role conscientiousness plays actually operates through the development of implementation plans. However, this is an empirical question. Proactive personality may also serve to impact the development of implementation plans in a similar vein. Proactive personality is considered a stable disposition towards enacting change and engaging in proactive behavior (Seibert, Crant, & Kraimer, 1999). Because implementation plans are the volitional process that follows a motivational assentation, it is possible that those who are more proactive by nature are more likely to develop these type of plans. Thus, individuals high in proactive personality may be more likely to develop implementation plans related to engaging in a target behavior.

In addition to the aforementioned individual variables, organizational variables such as social norms, aggregate unit CSE, and supervisor support may also play a role in

developing implementation plans. As organizations are multi-level systems, researchers should seek to understand how macro level factors play a role in shaping individual level factors, such as behavior. Klein and Kozlowski (2000) state that macro and micro perspectives alone cannot fully account for organizational behavior. The authors implore researchers to take a meso approach, which combines a macro and micro perspective, because it allows for a more comprehensive understanding of organizational behavior (Klein & Kozlowski, 2000). In the technology acceptance context, previous technology acceptance research has found a strong, positive relationship between social influence and behavioral intention at the micro level (Venkatesh et al., 2003). However, just as social influence may predict behavioral intention, social norms regarding behavior (i.e., technology use) could also impact the development of implementation plans. Specifically, if an individual feels little pressure from their work unit to use a particular piece of organizational technology, they may be less likely to develop implementation plans, even if they initially had a moderate behavioral intention. Higher-level computer self-efficacy may play a similar augmenting or hindering role. If individual computer self-efficacy predicts implementation plans, it may be likely that an individual's perception of a work unit's computer self-efficacy could also impact their development of implementation plans. As an example, an individual who is confident in their groups' ability to use computers and computer technology may be more likely to use some end-user technology (e.g. a communication software such as Lync) because they believe that others will also possess the ability to use the software as well; individuals will feel that developing implementation plans is a valuable use of time. Finally, perceptions of supervisor support may play a role in the development of implementation plans. Training

research has found that perceived supervisor support predicts training transfer intentions (Abdulkarim, Musaed, & Abdulla, 2009). However, no current research exists to see if supervisor support also plays a role in the development of implementation plans. Similar to the role of computer self-efficacy in the development of behavioral intentions and implementation plans, it is possible that perceived supervisor support may play a role in predicting both constructs.

Finally, future research should continue to search for moderators in the behavioral intention to implementation plans and implementation plans to behavior relationship. Other related individual differences, such as conscientiousness and proactive personality, may moderate the relationship between behavioral intention and implementation plans, such that conscientiousness individuals who have strong behavioral intentions are more likely to form implementation plans that those with strong behavioral intentions but are considered low in conscientiousness. Further, proactive personality may moderate the relationship between implementation plans to behavior such that proactive individuals with a high number of implementation plans are more likely to act on those plans than non-proactive individuals.

CHAPTER V

CONCLUSIONS

Organizations are continually seeking out new technology, such as end-user

technology, to assist in day to day workforce tasks. Knowledge management software,

organizational social networks, and organizational communication software are but a few

examples of an organization using resources to develop technological solutions and tools

to improve workforce performance and enable workforce communication. However, the

development and implementation of these tools alone do not guarantee their use.

Previous work has pointed to the importance of behavioral intention, as well as

antecedents of behavioral intention, in influencing technology usage behavior. This

research sought to understand how behavioral intention becomes actual use. These

findings demonstrated that behavioral intentions lead to the development of

implementation plans, which then lead to technology usage. Further, an employees'

confidence in their computer skills played a role in predicting both behavioral intentions

and implementation plans. Knowing this, organizations can attempt to ensure that

employees develop positive attitudes regarding organizational end-user software and

have a thorough understanding of how the technology can be used so that they may

development plans regarding how, where, when, and why to use target technologies.

REFERENCES

Abdulkarim, S., Musaed, A. F., & Abdulla, M. A. (2009). An empirical examination of the effects of self-efficacy, supervisor support and motivation to learn on transfer intention. *Management Decision, 47*(8), 1221-1244. doi: 10.1108/00251740910984514

Ajzen, I. (1985). From intentions to actions: A theory of planned behavior. In J. Kuhl & J. Beckman (Eds.), *Action-control: From cognition to behavior* (pp. 11-39). Heidelberg, Germany: Springer.

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179-211. doi: http://dx.doi.org/10.1016/0749-5978(91)90020-T

Arunkumar, S. (2008). A study on attitude and intention towards internet banking with reference to Malaysian consumers in klang valley region. *International Journal of Applied Management and Technology, 6*(1), 115-146.

Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review, 84*(2), 191-215. doi: 10.1037/0033-295X.84.2.191

Bandura, A. (1986a). The explanatory and predictive scope of self-efficacy theory. *Journal of Social and Clinical Psychology, 4*(3), 359-373.

Bandura, A. (1986b). *Social foundations of thought and action*. Englewood Cliffs, NJ: Prentice Hall.

Bandura, A. (1989). Regulation of cognitive processes through perceived self-efficacy. *Developmental Psychology, 25*(5), 729-735.

Bandura, A. (1995). *Self-efficacy in changing societies*. New York: Cambridge University Press.

Bandura, A. (1997). *Self-efficacy: The exercise of control.* New York: W. H. Freeman.

Bandura, A. (2001). Social cognitive theory: An agentic perspective. *Annual Review of Psychology, 52*(1), 1-26.

Bandura, A., & Cervone, D. (1983). Self-evaluative and self-efficacy mechanisms governing the motivational effects of goal systems. *Journal of Personality and Social Psychology, 45*(5), 1017-1028. doi: 10.1037/0022-3514.45.5.1017

Boekaerts, M., Maes, S., & Karoly, P. (2005). Self-regulation across domains of applied psychology: Is there an emerging consensus? *Applied Psychology: An International Review, 54*(2), 149-154. doi: 10.1111/j.1464-0597.2005.00201.x

Boekaerts, M., Pintrich, P. R., & Zeidner, M. (2000). *Handbook of self-regulation*. San Diego, CA US: Academic Press.

Brandstätter, V., Lengfelder, A., & Gollwitzer, P. M. (2001). Implementation intentions and efficient action initiation. *Journal of Personality and Social Psychology, 81*(5), 946-960. doi: 10.1037/0022-3514.81.5.946

Brickell, T. A., & Chatzisarantis, N. L. D. (2007). Using self-determination theory to examine the motivational correlates and predictive utility of spontaneous exercise implementation intentions. *Psychology of Sport and Exercise, 8*(5), 758-770. doi: 10.1016/j.psychsport.2006.11.001

Brown, K. G., & Charlier, S. D. (2013). An integrative model of e-learning use: Leveraging theory to understand and increase usage. *Human Resource Management Review 23*(1), 37-49. doi: 10.1016/j.hrmr.2012.06.004

Brusso, R. C., & Orvis, K. A. (2013). The impeding role of initial unrealistic goal-setting on videogame-based training performance: Identifying underpinning processes and a solution. *Computers in Human Behavior, 29*(4), 1686-1694. doi: http://dx.doi.org/10.1016/j.chb.2013.01.006

Burnham, K. P., & Anderson, D. R. (2002). *Model selection and multimodel inference: A practical information-theoretic approach* (2nd ed.). New York: Springer-Verlag.

Cameron, A. C., & Trivedi, P. K. (2013). Regression analysis of count data (2nd ed.). New York, NY: Cambridge University Press.

Chatzisarantis, N. L., & Hagger, M. S. (2007). Mindfulness and the intention-behavior relationship within the theory of planned behavior. *Personality and Social Psychology Bulletin, 33*(5), 663-676.

Cheung, R., & Vogel, D. (2013). Predicting user acceptance of collaborative technologies: An extension of the technology acceptance model for e-learning. *Computers & Education, 63*, 160-175. doi: 10.1016/j.compedu.2012.12.003

Chiaburu, D. S., & Marinova, S. V. (2005). What predicts skill transfer? An exploratory study of goal orientation, training self-efficacy and organizational supports. *International journal of training and development, 9*(2), 110-123.

Colquitt, J. A., LePine, J. A., & Noe, R. A. (2000). Toward an integrative theory of training motivation: A meta-analytic path analysis of 20 years of research. *Journal of Applied Psychology, 85*(5), 678-707. doi: 10.1037/0021-9010.85.5.678

Compeau, D. R., & Higgins, C. A. (1995). Computer self-efficacy: Development of a measure and initial test. *MIS Quarterly : Management Information Systems., 19*(2), 189-211.

Conner, M., Rodgers, W., & Murray, T. (2007). Conscientiousness and the intention-behavior relationship: Predicting exercise behavior. *Journal of Sport and Exercise Psychology, 29*(4), 518-533.

Costa, P. T., & McCrae, R. R. (1985). *The NEO ersonality inventory: Manual, Form S and Form R*: Psychological Assessment Resources.

Davis, F. D. (1985). *A technology acceptance model for empirically testing new end-user information systems: Theory and results*. Doctoral Dissertation. Retrieved from http://dspace.mit.edu/bitstream/handle/1721.1/15192/14927137.pdf?sequence=1

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319-340.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science, 35*(8), 982-1003.

Devaraj, S., & Kohli, R. (2003). Performance impacts of information technology: Is actual usage the missing link? *Management Science, 49*(3), 273-289.

Dwivedi, Y. K., Rana, N. P., Chen, H., & Williams, M. D. (2011). A meta-analysis of the Unified Theory of Acceptance and Use of Technology (UTAUT). *IFIP Advances in Information and Communication Technolog,* 366, 155-170.

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

Fletcher, J., & Banasik, J. (2001). Exercise self-efficacy. *Clinical excellence for nurse practitioners: the international journal of NPACE, 5*(3), 134-143.

Gist, M. E., Schwoerer, C., & Rosen, B. (1989). Effects of alternative training methods on self-efficacy and performance in computer software training. *Journal of Applied Psychology, 74*(6), 884-891. doi: 10.1037/0021-9010.74.6.884

Gnambs, T.(n.d.).   Retrieved January 26, 2015, from http://timo.gnambs.at/en/scripts/powerforsem

Goldberg, L. R. (1993). The structure of phenotypic personality traits. *American Psychologist, 48*(1), 26-34.

Gollwitzer, P. M. (1993). Goal achievement: The role of intentions. *European Review of Social Psychology, 4*(1), 141-185. doi: 10.1080/14792779343000059

Gollwitzer, P. M. (1999). Implementation intentions: Strong effects of simple plans. *American Psychologist, 54*(7), 493-503.

Gollwitzer, P. M., & Brandstätter, V. (1997). Implementation intentions and effective goal pursuit. *Journal of Personality and Social Psychology, 73*(1), 186-199.

Gollwitzer, P. M., & Sheeran, P. (2006). Implementation intentions and goal achievement: A meta-analysis of effects and processes. *Advances in Experimental Social Psychology, 38*, 69-119.

Gutiérrez-Doña, B., Lippke, S., Renner, B., Kwon, S., & Schwarzer, R. (2009). Self-efficacy and planning predict dietary behaviors in costa rican and south korean women: Two moderated mediation analyses. *Applied Psychology: Health and Well‑Being, 1*(1), 91-104. doi: 10.1111/j.1758-0854.2008.01001.x

Hedges, L. V., & Olkin, I. (1985). *Statistical methods for meta-analysis*. Orlando, FL: Academic Press.

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal, 6*(1), 1-55. doi: 10.1080/10705519909540118

Huang, Y. M. (2015). Exploring the factors that affect the intention to use collaborative technologies: The differing perspectives of sequential/global learners. *Australasian Journal of Educational Technology, 31*(3), 278-291. doi: doi:10.1111/j.1467-6494.1949.tb01237.x

Huang, J. L., Curran, P. G., Keeney, J., Poposki, E. M., & DeShon, R. P. (2012). Detecting and deterring insufficient effort responding to surveys. *Journal of Business and Psychology, 27*(1), 99-114.

Jasperson, J., Carter, P. E., & Zmud, R. W. (2005). A comprehensive conceptualization of post-adoptive behaviors associated with information technology enabled work systems. *MIS Quarterly, 29*(3), 525-557.

Judge, T. A., Jackson, C. L., Shaw, J. C., Scott, B. A., & Rich, B. L. (2007). Self-efficacy and work-related performance: The integral role of individual differences. *Journal of Applied Psychology, 92*(1), 107-127. doi: 10.1037/0021-9010.92.1.107

Kanfer, R., & Ackerman, P. L. (1989). Motivation and cognitive abilities: An integrative/aptitude-treatment interaction approach to skill acquisition. *Journal of Applied Psychology, 74*(4), 657-690.

Karahanna, E., Straub, D. W., & Chervany, N. L. (1999). Information technology adoption across time: A cross-sectional comparison of pre-adoption and post-adoption beliefs. *MIS Quarterly, 23*(2), 183-213.

Karoly, P. (1993). Mechanisms of self-regulation: A systems view. *Annual Review of Psychology, 44*, 23-52. doi: 10.1146/annurev.ps.44.020193.000323

Kim, K. H. (2005). The relation among fit indexes, power, and sample size in structural equation modeling. *Structural Equation Modeling, 12*(3), 368-390. doi: 10.1207/s15328007sem1203_2

King, W. R., & He, J. (2006). A meta-analysis of the technology acceptance model. *Information & Management, 43*(6), 740-755.

Klein, K. J., & Kozlowski, S. W. (2000). *Multilevel theory, research, and methods in organizations: Foundations, extensions, and new directions*. San Francisco, CA: Jossey-Bass.

Kozlowski, S. W., Gully, S. M., Brown, K. G., Salas, E., Smith, E. M., & Nason, E. R. (2001). Effects of training goals and goal orientation traits on multidimensional training outcomes and performance adaptability. *Organizational Behavior and Human Decision Processes, 85*(1), 1-31. doi: 10.1006/obhd.2000.2930

Latham, G. P., & Locke, E. A. (2007). New developments in and directions for goal-setting research. *European Psychologist, 12*(4), 290-300. doi: 10.1027/1016-9040.12.4.290

Latham, G. P., Winters, D. C., & Locke, E. A. (1994). Cognitive and motivational effects of participation: A mediator study. *Journal of Organizational Behavior, 15*(1), 49-63. doi: 10.1002/job.4030150106

Lawless, M. W., & Price, L. L. (1992). An agency perspective on new technology champions. *Organization Science, 3*(3), 342-355.

Lee, Y., Kozar, K. A., & Larsen, K. R. T. (2003). The technology acceptance model: Past, present, and future. *Communications of the Association for Information Systems, 12*(1), 752-780.

Legris, P., Ingham, J., & Collerette, P. (2003). Why do people use information technology? A critical review of the technology acceptance model. *Information & Management Information & Management, 40*(3), 191-204.

Lippke, S., Wiedemann, A., Ziegelmann, J., Reuter, T., & Schwarzer, R. (2009). Self-efficacy moderates the mediation of intentions into behavior via plans. *American Journal of Health Behavior, 33*(5), 521-529.

Lister, K., & Harnish, T. (2011). *The state of telework in the U.S.: How individuals, business, and government benefit*. The Telework Research Network Technical Report San Diego, CA.

Locke, E. A., & Latham, G. P. (2002). Building a practically useful theory of goal setting and task motivation: A 35-year odyssey. *American Psychologist, 57*(9), 705-717. doi: 10.1037//0003-066X.57.9.705

Locke, E. A., & Latham, G. P. (Eds.). (1990). *A theory of goal setting & task performance*. Englewood Cliffs, NJ: Prentice-Hall, Inc.

Maddux, J. E., & Volkmann, J. (2010). Self-efficacy. In R. H. Hoyle (Ed.), *Handbook of personality and self-regulation* (pp. 315-331). Oxford: Wiley-Blackwell.

Martocchio, J. J., & Judge, T. A. (1997). Relationship between conscientiousness and learning in employee training: Mediating influences of self-deception and self-efficacy. *Journal of Applied Psychology, 82*(5), 764-773. doi: 10.1037/0021-9010.82.5.764

McAfee, A. P. (2011). *Shattering the myths about enterprise 2.0*. MIT Center for Digital Business Technical Report Cambridge, MA.

Meade, A. W., & Craig, S. B. (2012). Identifying careless responses in survey data. *Psychological Methods, 17*(3), 437-455. doi: 10.1037/a0028085

Michie, S., Johnston, M., Francis, J., Hardeman, W., & Eccles, M. (2008). From theory to intervention: Mapping theoretically derived behavioural determinants to behaviour change techniques. *Applied Psychology: An International Review, 57*(4), 660-680. doi: 10.1111/j.1464-0597.2008.00341.x

Miller, L., Mandzuk, C., Frankel, D., McDonald, A., & Bello, B. (2013). *Astd 2013 state of the industry*. American Society for Training and Development Technical Report Alexandria, VA.

Moynihan, L. M., Roehling, M. V., LePine, M. A., & Boswell, W. R. (2003). A longitudinal study of the relationships among job search self-efficacy, job interviews, and employment outcomes. *Journal of Business and Psychology, 18*(2), 207-233.

Nagin, D. (2005). *Group-based modeling of development*: Harvard University Press.

Oettingen, G., Wittchen, M., & Gollwitzer, P. M. (2013). Regulating goal pursuit through mental contrasting and implementation intentions. In E. Locke & G. Latham (Eds.), *New developments in goal setting and task performance* (pp. 523-548). Hoboken, NJ: Taylor and Francis.

Orbell, S., & Sheeran, P. (1998). 'Inclined abstainers': A problem for predicting health-related behaviour. *British Journal of Social Psychology, 37*(2), 151-165.

Orvis, K. A., Orvis, K. L., Belanich, J., & Mullin, L. N. (2007). The influence of trainee gaming experience on affective and motivational learner outcomes of videogame-based training environments. In H. O'Neil & R. Perez (Eds.), *Computer games and team and individual learning* (pp. 125-143). Oxford, U.K.: Elsevier.

Parks-Stamm, E. J., Gollwitzer, P. M., & Oettingen, G. (2007). Action control by implementation intentions: Effective cue detection and efficient response initiation. *Social Cognition, 25*(2), 248-266.

Phillips, J. M., & Gully, S. M. (1997). Role of goal orientation, ability, need for achievement, and locus of control in the self-efficacy and goal--setting process. *Journal of Applied Psychology, 82*(5), 792-802. doi: 10.1037/0021-9010.82.5.792

Pintrich, P. R. (2000). The role of goal orientation in self-regulated learning. In M. Boekaerts, P. R. Pintrich & M. Zeidner (Eds.), *Handbook of Self-Regulation.* (pp. 451-502). San Diego, CA US: Academic Press.

Pintrich, P. R. (2004). A conceptual framework for assessing motivation and self-regulated learning in college students. *Educational Psychology Review, 16*(4), 385-407.

Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods, 40*(3), 879-891. doi: 10.3758/BRM.40.3.879

Preacher, K. J., Rucker, D. D., & Hayes, A. F. (2007). Addressing moderated mediation hypotheses: Theory, methods, and prescriptions. *Multivariate Behavioral Research, 42*(1), 185-227.

Raftery, A. E. (1995). Bayesian model selection in social research. *Sociological Methodology, 25*, 111-164.

Rhodes, R. E., Courneya, K. S., & Hayduk, L. A. (2002). Does personality moderate the theory of planned behavior in the exercise domain? *Journal of Sport & Exercise Psychology, 24*(2), 120-132.

Rise, J., Thompson, M., & Verplanken, B. (2003). Measuring implementation intentions in the context of the theory of planned behavior. *Scandinavian Journal of Psychology, 44*(2), 87-95. doi: 10.1111/1467-9450.00325

Schepers, J., & Wetzels, M. (2007). A meta-analysis of the technology acceptance model: Investigating subjective norm and moderation effects. *Information & Management, 44*(1), 90-103.

Scholz, U., Nagy, G., Göhner, W., Luszczynska, A., & Kliegel, M. (2009). Changes in self-regulatory cognitions as predictors of changes in smoking and nutrition behaviour. *Psychology and Health, 24*(5), 545-561.

Schumacker, R., & Lomax, R. (2004). *A beginner's guide to structural equation modeling* (Vol. 2): Lawrence Erlbaum.

Schwarzer, R., Richert, J., Kreausukon, P., Remme, L., Wiedemann, A. U., & Reuter, T. (2010). Translating intentions into nutrition behaviors via planning requires self-efficacy: Evidence from thailand and germany. *International Journal of Psychology, 45*(4), 260-268. doi: 10.1080/00207591003674479

Seibert, S. E., Crant, J. M., & Kraimer, M. L. (1999). Proactive personality and career success. *Journal of Applied Psychology, 84*(3), 416-427.

Shadish, W. R., Cook, T. D., & Campbell, D. T. (2002). *Experimental and quasi-experimental designs for generalized causal inference*. Boston, MA: Houghton Mifflin.

Sheeran, P. (2002). Intention—behavior relations: A conceptual and empirical review. *European Review of Social Psychology, 12*(1), 1-36. doi: 10.1080/14792772143000003

Sheeran, P., & Orbell, S. (1998). Do intentions predict condom use? Metaanalysis and examination of six moderator variables. *British Journal of Social Psychology, 37*(2), 231-250. doi: 10.1111/j.2044-8309.1998.tb01167.x

Sheeran, P., & Silverman, M. (2003). Evaluation of three interventions to promote workplace health and safety: Evidence for the utility of implementation intentions. *Social Science & Medicine, 56*(10), 2153-2163. doi: 10.1016/s0277-9536(02)00220-4

Sheeran, P., Webb, T., & Gollwitzer, P. M. (2005a). The interplay between goal intentions and implementation intentions. *Personality and Social Psychology Bulletin, 31*(1), 87-98.

Sheeran, P., Webb, T. L., & Gollwitzer, P. M. (2005b). The interplay between goal intentions and implementation intentions. *Personality and Social Psychology Bulletin, 31*(1), 87-98.

Sitzmann, T., & Ely, K. (2011). A meta-analysis of self-regulated learning in work-related training and educational attainment: What we know and where we need to go. *Psychological Bulletin, 137*(3), 421-442.

Sniehotta, F. F. (2009). Towards a theory of intentional behaviour change: Plans, planning, and self-regulation. *British Journal of Health Psychology, 14*(2), 261-273.

Sniehotta, F. F., Scholz, U., & Schwarzer, R. (2005). Bridging the intention–behaviour gap: Planning, self-efficacy, and action control in the adoption and maintenance of physical exercise. *Psychology & Health, 20*(2), 143-160.

Sniehotta, F. F., Schwarzer, R., Scholz, U., & Schüz, B. (2005). Action planning and coping planning for long-term lifestyle change: Theory and assessment. *European Journal of Social Psychology, 35*(4), 565-576. doi: 10.1002/ejsp.258

Stajkovic, A. D., & Luthans, F. (1998). Self-efficacy and work-related performance: A meta-analysis. *Psychological bulletin, 124*(2), 240-261. doi: 10.1037/0033-2909.124.2.240

Steel, P. (2007). The nature of procrastination: A meta-analytic and theoretical review of quintessential self-regulatory failure. *Psychological Bulletin, 133*(1), 65-94. doi: 10.1037/0033-2909.133.1.65

Steel, R. P., & Ovalle, N. K. (1984). A review and meta-analysis of research on the relationship between behavioral intentions and employee turnover. *Journal of Applied Psychology, 69*(4), 673-686.

Straub, D., Limayem, M., & Karahanna-Evaristo, E. (1995). Measuring system usage: Implications for IS theory testing. *Management Science, 41*(8), 1328-1342.

Thompson, R. L., Higgins, C. A., & Howell, J. M. (1991). Personal computing: Toward a conceptual model of utilization. *MIS Quarterly, 15*(1), 125-143.

Venkatesh, V. (1999). Creation of favorable user perceptions: Exploring the role of intrinsic motivation. *MIS Quarterly, 23*(2), 239-260.

Venkatesh, V. (2000). Determinants of perceived ease of use: Integrating control, intrinsic motivation, and emotion into the technology acceptance model. *Information Systems Research, 11*(4), 342-365. doi: 10.1287/isre.11.4.342.11872

Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision Sciences, 39*(2), 273-315. doi: 10.1111/j.1540-5915.2008.00192.x

Venkatesh, V., & Davis, F. D. (1996). A model of the antecedents of perceived ease of use: Development and test. *Decision Sciences, 27*(3), 451-482.

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science, 46*(2), 186-204.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425-478.

Wagenmakers, E.-J., & Farrell, S. (2004). Aic model selection using akaike weights. *Psychonomic Bulletin & Review, 11*(1), 192-196.

Webb, T. L., & Sheeran, P. (2006). Does changing behavioral intentions engender behavior change? A meta-analysis of the experimental evidence. *Psychological Bulletin, 132*(2), 249-268.

Webb, T. L., & Sheeran, P. (2008). Mechanisms of implementation intention effects: The role of goal intentions, self-efficacy, and accessibility of plan components. *British Journal of Social Psychology, 47*(3), 373-395. doi: 10.1348/014466607X267010

Westland, J. C. (2010). Lower bounds on sample size in structural equation modeling. *Electronic Commerce Research and Applications, 9*(6), 476-487. doi: 10.1016/j.elerap.2010.07.003

Wieber, F., Odenthal, G., & Gollwitzer, P. M. (2010). Self-efficacy feelings moderate implementation intention effects. *Self and Identity, 9*(2), 177-194.

Wolters, C. A. (2003). Regulation of motivation: Evaluating an underemphasized aspect of self-regulated learning. *Educational Psychologist, 38*(4), 189-205.

Wood, R., & Bandura, A. (1989). Social cognitive theory of organizational management. *Academy of Management Review, 14*(3), 361-384. doi: 10.5465/AMR.1989.4279067

APPENDIX A

NOTIFICATION STATEMENT

PROJECT TITLE: Lync Usage

RESEARCHERS: Assistant Professor Richard Landers, Ph.D. of the Department of Psychology in the College of Sciences, head of the Technology iN Training Laboratory (TNTLab) is the Responsible Project Investigator (RPI). You can reach him at rnlanders@odu.edu. Robert Brusso is also an investigator. You can reach him at Robert.Brusso@icfi.com.

DESCRIPTION OF RESEARCH STUDY: In this study, you will complete a survey about your Lync usage as an ICF employee. Once complete, your responses will be paired with your queried Lync usage by an ICF database manager via your employee ID. Once these pairings are complete, your employee ID will be removed from the dataset.

EXCLUSIONARY CRITERIA: You must be full-time employee at ICF within the Technology Management Solutions (TMS) division.

RISKS AND BENEFITS: Your participation in this study is completely voluntary and will be confidential. You will never be identified in any research reports resulting from this study, and your responses will only be reported in aggregate with other respondents. By completing this study, you will entered to win one of three Amazon gift cards redeemable at www.Amazon.com. The denominations of these gift cards are $100, $50, and $25 and winners will be drawn at random following the completion of data collection.

APPENDIX B

BACKGROUND INFORMATION

Instructions: Please answer the following questions concerning your demographic and employment information.

1. Employee ID:

   _____

2. Years employed by ICF:

   _____

3. Your current title:

   _____

4. What is your current age (years)?

   _____ Age

5. What is your gender:

   ☐Male

   ☐Female

6. What is your ethnicity?

   ☐ White/Caucasian

   ☐ Black/African American

   ☐ Hispanic or Latino

   ☐ Asian

   ☐ American Indian or Alaska Native

   ☐ Native Hawaiian or Pacific Islander

   ☐ Other_____

APPENDIX C

BEHAVIORAL INTENTIONS

Instructions: Indicate the degree to which you agree or disagree with the statements below. Circle only one of the options on the right.

Item	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I intend to use Lync within the next month.	1	2	3	4	5
I predict I would use the system in the next month.	1	2	3	4	5
I plan to use Lync in the next month.	1	2	3	4	5

APPENDIX D

IMPLEMENTATION PLANS

Instructions: For the following items, please respond using the timeframe of the next month and indicate the degree to which you agree or disagree with the statements below. Circle only one of the options on the right.

For the next month…	Zero	A Few	Many	Every
…I have a plan for […] type(s) of tasks where I'm going to use Lync. [1]	1	2	3	4
…I have a plan for […] feature(s) of Lync I am going to use (e.g. meeting scheduler, file sharer, video communicator, text-based communicator, audio communicator, whiteboard, screen sharer). [1]	1	2	3	4
…I have a plan for […] kind(s) of activities I am going to use Lync to accomplish (e.g. holding a meeting, communicating with others, sharing screens, and sharing documents). [1]	1	2	3	4
…I have a plan to utilize [..] feature(s) of Lync (e.g. starting a new text-based conversation, initiating screen sharing, scheduling a meeting, initiating a video call, and initiating an audio call). [1]	1	2	3	4
…I have a plan for […] situation(s) I will use Lync for (e.g. holding a meeting, communicating with others, sharing screens, and sharing documents). [2]	1	2	3	4
…I have a plan for […] way(s) I am going to use Lync to communicate to co-workers. [2]	1	2	3	4
…I have a plan for […] way(s) I am going to use Lync to share content (e.g. files, video, and meetings). [2]	1	2	3	4
…I have committed myself to [..] situation(s) when I will use Lync (e.g. holding a meeting, communicating with others, sharing screens, and sharing documents). [2]	1	2	3	4
…I have committed myself to [..] activity/activities when I will use Lync (e.g., meetings, text-based, audio-based, or video-based conversations, or screen sharing). [2]	1	2	3	4

[1] Adapted from Rise, Thompson, and Verplanken (2003)

[2] Adapted from Bricknell & Chatzisarantis (2007)

APPENDIX E

COMPUTER SELF-EFFICACY

Instructions: Often in our jobs we are told about software packages that are available to make work easier. For the following questions, imagine that you were given a new software package for some aspect of your work. It doesn't matter specifically what this software package does, only that it is intended to make your job easier and that you have never used it before.

The following questions ask you to indicate whether you could use this unfamiliar software package under a variety of conditions. For each item, please indicate the degree to which you agree or disagree with each statement below in reference to the stem: "I could complete the job using the software package…" Circle only one of the options on the right.

STEM: I could complete the job using the software package…

Item	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
…if there was no one around to tell me what to do as I go.	1	2	3	4	5
…if I had never used a package like it before.	1	2	3	4	5
…if I had only the software manuals for reference.	1	2	3	4	5
…if I had seen someone else using it before trying it myself.	1	2	3	4	5
…if I could call someone for help if I got stuck.	1	2	3	4	5
…if someone else had helped me get started.	1	2	3	4	5
…if I had a lot of time to complete the job for which the software was provided.	1	2	3	4	5
…if I had just the built-in help facility for assistance.	1	2	3	4	5
…if someone showed me how to do it first.	1	2	3	4	5
…if I had used similar packages before this one to do the same job.	1	2	3	4	5

APPENDIX F

DEBRIEF

Thank you for participating in the Lync Usage survey. We appreciate your responses and participation. The results of this survey will help to demonstrate current Lync usage behavior and may help to uncover ways to increase Lync usage. Should you have any questions, please feel free to contact Dr. Richard Landers (rnlanders@odu.edu) or Robert Brusso (Robert.brusso@icfi.com).

VITA

ROBERT CONRAD BRUSSO
Department of Psychology
250 Mills Godwin Building
Old Dominion University
Norfolk, VA 23529-0267

Education

Old Dominion University, Norfolk, VA; Doctor of Philosophy, Industrial-Organizational Psychology; Expected Dec. 2015
Old Dominion University, Norfolk, VA; Masters of Science, Psychology, Dec. 2010
Virginia Tech, Blacksburg, VA; Bachelor of Science, Psychology; May 2007

Work Experience

Senior Associate, ICF International, March 2014 – Current
Associate, ICF International, May 2011 – March 2014
Instructor, Old Dominion University, Jan. 2011 – May 2012
Teaching Assistance, Old Dominion University, Jan. 2009 – Dec. 2010
Research Assistant, Old Dominion University, Sep. 2007 – May 2011

Research

Wisher, R., **Brusso, R.C.,** Paddock, A., & Hatfield, J. (2015). Formulating Best Practices and Guidelines for Emerging e-Learning Technologies. In M. Ally & B. Kahn, *International Handbook of E-learning.* (Vol. 1, pp. 127-138). New York, NY: Routledge.

Brusso, R. C., Cigularov, K. P., & Callan, R. C. (2014). Longitudinal research in occupational stress: A review of methodological issues. In P. Y. Chen & C. L. Cooper (Eds.), *Wellbeing: A complete reference guide. Work and wellbeing* (Vol. 3, pp. 381-407). Wiley-Blackwell.

Brusso, R. C., & Orvis, K. A. (2013). The impeding role of initial unrealistic goal-setting on videogame-based training performance: Identifying underpinning processes and a solution. *Computers in Human Behavior, 29*(4), 1686-1694. doi: http://dx.doi.org/10.1016/j.chb.2013.01.006

Bauer, K. N., **Brusso, R. C.**, & Orvis, K. A. (2012). Using adaptive difficulty to optimize videogame-based training performance: The moderating role of personality. *Military Psychology, 24*(2), 148-165. doi: 10.1080/08995605.2012.672908

Brusso, R. C., Orvis, K. A., Bauer, K. N., & Tekleab, A. G. (2012). Interaction among self-efficacy, goal orientation, and unrealistic goal-setting on videogame-based training performance. *Military Psychology, 24*(1), 1-18. doi: 10.1080/08995605.2012.639669

Orvis, K. A., **Brusso, R.C.**, Wasserman, M. E., & Fisher, S.L. (2011). E-nabled for e-learning? The moderating role of personality in determining the optimal degree of learner control in an e-learning environment. *Human Performance, 24*(1)*, 60 – 78.* doi: 10.1080/08959285.2010.530633