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EXPLORING THE HOWS AND THE WHOS: THE EFFECTS OF SELF-REGULATION
PROMPTING AND GOAL ORIENTATION ON THE E-LEARNING PROCESS

by

LAUREN E. BENISHEK
B.S., Virginia Polytechnic Institute and State University, 2007

A dissertation submitted in partial fulfillment of the requirements
for the degree of Doctor of Philosophy
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Major Professor: Eduardo Salas

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ABSTRACT

This study investigated the effects that self-regulation prompts and goal orientation may exhibit on self-regulatory processes and subsequent learning. Specifically, a moderated mediation model was developed to explain how self-regulation prompts interact with performance goal orientation to affect two mediational processes, time on task and self-regulatory activity, and ultimately impact learning within a learner-controlled e-learning environment. To assess these hypotheses, an online Microsoft Excel instructional program was developed wherein 197 participants had control over when and where they completed training, the content they reviewed, the delivery medium (text-based or video-based), and the sequencing and pace at which they progressed through training. Participants in the experimental condition were periodically asked questions (i.e., self-regulation prompts) designed to encourage self-assessment of learning progress and strategies. All participants completed questionnaires before and after training. Findings did not support the hypothesized model. Implications and limitations as well as recommendations for future research will be discussed.

This dissertation is dedicated to the village that raised me.
Especially my grandparents, Elise Benishek, Mike Sinclair, and Jack and Mary Coulter,
of whose pride in me I have tried to be deserving.

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TABLE OF CONTENTS

LIST OF FIGURES	ix
LIST OF TABLES	x
CHAPTER ONE: INTRODUCTION.....	1
Statement of the Problem	1
Learner Control.....	2
Designing Training to Stimulate Self-Regulation	6
Individual Differences	8
Purpose of the Current Study	11
CHAPTER TWO: LITERATURE REVIEW.....	14
Self-Regulatory Processes.....	17
Hypothesis 1a.....	20
Hypothesis 1b	20
Learning	20
Cognitive Load Theory.....	21
Hypothesis 2	25
Hypothesis 3a.....	25
Hypothesis 3b	26
Goal Orientation	26
Hypothesis 4a.....	30
Hypothesis 4b	30
Control Variables	31
Cognitive ability.	31
CHAPTER THREE: METHOD	32
Needs Analysis	32
Participants	35
Power analysis	36
Experimental Design and Procedure	40
Measures.....	42
Prove performance goal orientation.....	42
Learning and knowledge.....	43
Time.....	43

Self-regulatory activity	44
Cognitive ability.	44
Manipulation check	45
Internal Review Board Submission Decision.....	45
Data Analysis	46
CHAPTER FOUR: RESULTS	47
Data Filtering.....	47
Correlational Results	49
Reliability	51
Between Group Comparisons.....	52
Manipulation Check	54
Tests of Hypotheses	55
Direct effect of prompts.....	55
Indirect effect of prompts	56
Conditional effect of prove performance goal orientation	56
Exploratory Analysis.....	58
Obligation to self-regulate	58
Manipulation saliency.....	60
Issues of reliability.....	61
CHAPTER FIVE: DISCUSSION.....	64
Post Hoc Investigation	65
Methodological factors	65
Uniform feelings of obligation to self-regulate	67
Manipulation saliency and strength	68
Theoretical Implications.....	68
Practical Implications	70
Limitations	71
Future Directions.....	72
Conclusion.....	74
APPENDIX A: SELF-REGULATION PROMPTS	76
APPENDIX B: TECHNOLOGY READINESS INDEX	78
APPENDIX C: PROVE PERFORMANCE GOAL ORIENTATION SCALE	80

APPENDIX D: MICROSOFT EXCEL 2013 KNOWLEDGE SCALE.....	82
APPENDIX E: SELF-REGULATORY ACTIVITY SCALE.....	86
APPENDIX F: ACT & SAT SCORES COMPARISON TABLES	88
APPENDIX G: 1600 AND 2400 SAT FORMAT COMPARISON TABLE.....	91
APPENDIX H: MANIPULATION CHECK.....	93
APPENDIX I: UCF IRB LETTER	95
REFERENCES	97

LIST OF FIGURES

Figure 1. Relationships between Study Variables	16
Figure 2. Hypothesized Interaction between Self-Regulation Prompts, Prove Performance Goal Orientation, and Effort	30

LIST OF TABLES

Table 1. Conceptual and Operational Definitions of Study Variables.....	15
Table 2. Summary of Study Hypotheses.....	16
Table 3. Average Overall and Subsection Scores on the Needs Analysis Declarative Knowledge Test.....	33
Table 4. Participant Demographics as a Percentage of the Sample.....	36
Table 5. Sample Size, Means, Standard Deviations, Reliabilities, and Zero-Order Correlations between Study Variables.....	50
Table 6. Means, Standard Deviations, Reliabilities, and Zero-Order Correlations between Self-Regulatory Activity Subscales.....	51
Table 7. Results of One-Way Analysis of Variance (ANOVA) between Data Sources and Study Variables.....	53
Table 8. Data Source Descriptive Statistics for Study Variables.....	53
Table 9. Results of Independent Samples T-tests between Study Conditions.....	54
Table 10. Group Responses to Manipulation Check Items.....	55
Table 11. Predictors of Time on Task, Self-regulatory Activity, and Learning.....	57
Table 12. Conditional Indirect Effects of Prompts in Relation to Learning.....	58
Table 13. Results of the Chi-Square for Independence Tests between Group Responses to Manipulation Check Items.....	59
Table 14. Predictors of Time on Task, Self-regulatory Activity, and Learning within the Restricted Sample.....	61
Table 15. Predictors of Concentration, Metacognition, Motivation, and Learning.....	63
Table 16. Concordance between ACT Composite Score and Sum of SAT Critical Reading and Mathematics Scores.....	89
Table 17. Concordance between ACT Combined English/Writing Score and SAT Writing Score.....	90
Table 18. A Score Comparison between the ACT, Old SAT, and New SAT Reasoning Tests...	92

CHAPTER ONE: INTRODUCTION

Statement of the Problem

Computers and other electronic technologies have become popular instructional tools in both educational and organizational settings (Salas & Cannon-Bowers, 2001; Sitzmann, Kraiger, Steward, & Wisher, 2006). Driven by advances in learning technologies, as well as a desire for reduced costs, web-based learning, multimedia, mobile, and other forms of computer-based instruction (CBI) are an increasingly common means for delivering training (Brown & Ford, 2002; DeRouin, Fritzsche, & Salas, 2004, 2005; Eschenmann, 2012; Hughes, Day, Wang, Schuelke, Arsenault, Harkrider, & Cooper, 2013; Kosarzycki, Salas, DeRouin, & Fiore, 2003; Orvis, Brusso, Wasserman, & Fisher, 2010). In fact, the American Society for Training and Development (ASTD) reported a steady increase in the use of technology-based instructional delivery methods from 30.3% in 2006 to 37.3% in 2011 (L. Miller, 2012). Underscoring these trends, 86% of organizations planned to invest in e-learning (i.e., the use of electronic technologies to deliver information and facilitate the development of skills and knowledge; L. Miller, 2012) in 2013 (Franko & Rimmer, 2013). The increasing prevalence in the use of electronic technology to deliver training has been termed the “e-Learning Revolution” (Galagan, 2000, p. 25). Growth and development of learning technologies have provided learners and instructional designers with new educational opportunities previously unavailable (Eschenmann, 2012), giving rise to the use of web-based training and synthetic learning environments (SLEs)

such as computer-based simulations, games, and virtual-reality environments (Behrend & Thompson, 2011; Cannon-Bowers & Bowers, 2009; Wilson et al., 2009).

Learner Control. Irrespective of the form of instructional delivery, learner control is an inherent element of many types of e-learning, including CBI and SLEs (Bell & Kozlowski, 2002; Ely, Sitzmann, & Falkiewicz, 2009; Hughes et al., 2013). *Learner control* is not an all or nothing instructional design characteristic; rather, it refers to the *degree to which* learners are able to manipulate the learning environment (Brown, 2001; Carolan, Hutchins, Wickens, & Cumming, 2014; DeRouin et al., 2004, 2005; Fisher, Wasserman, & Orvis, 2010; Gay, 1986; Granger & Levine, 2010; Kraiger & Jerden, 2007; Orvis, Fisher, & Wasserman, 2009; Schmidt & Ford, 2003). Karim and Behrend (2013) have identified two major classes of learner control: instructional and scheduling control. Instructional control allows learners to manipulate various aspects of the instruction itself, including pace, sequence, content, guidance, and design of the training content. Scheduling control, on the other hand, allows learners to control the learning environment including the location and time when they will participate in training. Scheduling control is believed to be related to engagement since learners are able to select times when and locations where they may be best able to attend to training. It is also the scheduling control aspect that draws many people to learner controlled training as it provides greater flexibility to fit learning opportunities into overly scheduled lives. Historically, however, learner control has been most frequently operationalized in research as learners' control over the pace (e.g., Arnone & Grabowski, 1992; Brown, 2001; Fisher, Wasserman, & Orvis, 2010; Gray, 1987; Orvis, Fisher, & Wasserman, 2009; Schmidt & Ford, 2003; Sitzmann & Ely, 2010) and sequencing (e.g., Arnone & Grabowski, 1992; Aly, Elen, & Willems, 2005; Bell & Kozlowski, 2002; Fisher

et al., 2010; Gray, 1987; Orvis et al., 2009; Schmidt & Ford, 2003) of their instruction. Pacing control allows learners to choose how much time they spend navigating the training content. Sequencing control allows learners to choose the order in which they navigate training content.

In learner-controlled training, learners actively participate in the learning process (Carolan et al., 2014; Frese & Altmann, 1989; Salas & Cannon-Bowers, 2001) and have the onus to regulate and direct their own learning (Bell & Kozlowski, 2008). Although not uniformly the case, technology-based learning environments often provide learners high levels of control over their instruction (Bell & Kozlowski, 2002; DeRouin et al., 2004; Ely et al., 2009; Granger, 2012), allowing them to make certain decisions regarding their learning experiences such as how, what, when, and where they learn. The inherent potential for flexibility with learner-controlled designs is appealing to organizations operating in our fast-paced, technology-dense culture and the popularity of e-learning technologies characterized by learner control is increasing in organizational and educational settings (Sugrue & Rivera, 2005). Unfortunately, research on learner-controlled instruction has not kept pace with the burgeoning use of e-learning technology utilized in training and instruction, and the current evidence base is equivocal with regards to its advantages (e.g., Carolan et al, 2014; Kraiger & Jerden, 2007). Additional research is merited in order to confirm many of the propositions and assumptions made about learner controlled e-learning (Granger, 2012; Granger & Levine, 2010), as well as to elucidate the conditions under which learner-controlled training is appropriate and efficacious.

The rationale for the use of learner control in training is supported by the constructivist educational philosophy (Lee & Lee, 2008). The underlying premise of constructivist teaching methods is the belief that learning is a dynamic process in which learners are active sense makers

seeking to build coherent and organized knowledge through exploration and interaction with the environment (Jonassen, 1991; Mayer, 2004; S. Park, 2008; Rovai, 2004). This type of active involvement in the learning process is believed to facilitate a deeper processing of training content as it pushes learners to think critically and evaluate how the information provided in training can be used to help them achieve learning objectives (Patterson, 2000). The positive benefits of active participation on learning outcomes are supported by the literature, suggesting that the learning process is triggered by learners' intentional acts rather than mandated curricula (see Bouchard, 2009). In fact, Cross (1981) estimated that as much as 70 percent of adult learning is self-directed rather than instructor-assisted.

A second argument favoring learner control rests on the assumption that learners have a better understanding of their own learning preferences, skills, and deficiencies than instructional designers (Carrier, 1984) and are, therefore, equipped to make more effective decisions regarding their training and learning than educators (Niemic, Silkorski, & Walberg, 1996). From this perspective, learner control is seen as advantageous because it allows learners the opportunity to adapt their instruction to match their own preferences and needs (Mager, 1964; Merrill, 1975, 1980).

Despite the intuitive potential advantages of learner control (Kinzie & Sullivan, 1989), a growing body of empirical evidence suggests that learners do not always effectively use control opportunities (Bell & Kozlowski, 2002; Brown, 2001; Crooks, Klein, Jones, & Dwyer, 1996; Kopcha & Sullivan, 2008). Learner control may provide an opportunity for individuals to commit less effort (Clark, 1983, 1984) and other self-regulatory activities to the learning process; thereby resulting in muted knowledge, skill, and attitude changes. Even when learners are

motivated to commit resources to learning, making good instructional decisions in a learner-controlled program is not always simple; the cognitive resources required to weigh options may interfere with the learning process itself (Bannert, 2002; Freitag & Sullivan, 1995; van Merriënboer, Schuurman, de Croock, & Paas, 2002). Indeed, empirical evidence shows that learners are poor judges of their own learning (Koriat & Bjork, 2005) and often adopt poor learning strategies, especially in learner-controlled instruction (Bjork, 1994; Kraiger & Jerden, 2007). Given that self-regulation is crucial for learning from CBI (Bell & Kozlowski, 2002), failure to self-regulate effectively when given freedom in training may explain learners' poor instructional choices (Bell & Kozlowski, 2002; DeRouin et al., 2005; Kauffman, 2004; Kraiger & Jerden, 2007; Sitzmann, Bell, Kraiger, & Kanar, 2009).

Self-Regulation. *Self-regulation* refers to learners' self-generated thoughts and behaviors that are systematically directed toward the attainment of learning goals over time (Karoly, 1993; Schunk & Zimmerman, 2003). Examination of the construct of self-regulation has been conducted across a wide range of literatures including education (Paas, 1992; Sungur, 2007; Sweller, van Merriënboer, & Paas, 1998), cognitive science (Hong, 1995), instructional psychology (Paas, Renkl, & Sweller, 2004; Steinberg, 1989), human factors (Hart & Staveland, 1988), and industrial-organizational psychology (Ely et al., 2009; Fisher & Ford, 1998; Kanfer & Ackerman, 1989; Sitzmann & Ely, 2010; Yeo & Neal, 2004, 2008). Research has established metacognition, cognitive strategies, and motivation as hallmarks of achievement and important elements of *self-regulated learning* (e.g., Butler & Winne, 1995; Colquitt, LePine, & Noe, 2000; Perry, 2002; Pintrich, 2000; Schraw, Kauffman, & Lehman, 2002; Zimmerman, 1989, 1994); that is, learners' intentional efforts to manage and direct learning activities (DuBois & Staley,

1997; Kauffman, 2004; Winne, 1995). Theory proposes that self-regulation is malleable and influenced by environmental forces (Carver & Scheier, 1990; Kanfer & Ackerman, 1989; Schunk & Zimmerman, 1994; Winne, 1995). Personal, behavioral, and situational factors interact and change throughout the learning process, affecting how learners self-regulate (Bandura, 1986, 1997; Zimmerman, 1994). Monitoring these factors allows learners to adapt their learning strategies and control their cognitions, affect, and behaviors during training (Pintrich, 2000; Schunk & Zimmerman, 2003). However, learners do not consistently participate in successful self-regulation during training (Butler & Winne, 1995; Hüber, Nückles, & Renkl, 2006; Kauffman, 2004). They are often distracted by off-task thoughts, fail to devote enough effort to learning, and adopt suboptimal learning strategies (Berthold, Nückles, & Renkl, 2007; Brown, 2001; DeRouin et al., 2005; Kanfer & Ackerman, 1989; Kauffman, 2004; Sitzmann, Ely, Brown, & Bauer, 2010; Winne, 1995). However, as reviewed below, some research indicates that it may be possible to incorporate strategies into the design of learner-controlled training that assist learners with effective self-regulation.

Designing Training to Stimulate Self-Regulation. In general, training researchers have investigated the situational and contextual factors that influence training effectiveness (Narayan & Steele-Johnson, 2007), including organizational climate, commitment, and career planning (e.g., Colquitt et al., 2000), supervisory and peer support (e.g., Blume, Ford, Baldwin, & Huang, 2010; Mathieu & Martineau, 1997), and work policies (Mathieu & Martineau, 1997). Recent work has examined a number of training design factors that enhance learning and transfer in learner-controlled training environments, including exploratory learning (Bell & Kozlowski, 2008), error-encouragement framing (Bell & Kozlowski, 2008; Keith & Frese, 2005), and self-

regulation prompting (Sitzmann et al., 2009; Sitzmann & Ely, 2010). When considered together, these studies indicate that design factors influence the effectiveness of learner-controlled training. Training researchers have also explored the interrelationships among various individual difference variables and training outcomes (Blume et al., 2010; Brown, 2001; Brown, 2005; Ely et al., 2009; Fisher & Ford, 1998; Ford, Smith, Weissbein, Gully, & Salas, 1998; Fisher et al., 2010; Schmidt & Ford, 2003; Sitzmann et al., 2009). Collectively, findings from extant research indicate that while certain training interventions are helpful for some learners, they are not necessarily beneficial to others. Similar findings have also been observed within learner-controlled training (e.g., Brown, 2001; Fisher et al., 2010; Schmidt & Ford, 2003; Sitzmann et al., 2009) but much is still unknown about how learner-controlled instruction can be designed to enhance learning and which learners benefit most from different design features.

One training design approach involves encouraging self-regulation via question-based prompts (Berthold, Nückles, & Renkl, 2004, 2007; Sitzmann et al., 2009; Sitzmann & Ely, 2010). *Self-regulation prompts* are intended to supersede learners' tendencies to exert less effort during training, become distracted, or employ inefficient learning strategies (Berthold et al., 2007; Kauffman, 2004; Sitzmann & Ely, 2010). Prompts are questions or hints that induce productive learning processes (Berthold et al., 2004, 2007). They can be incorporated into training design as *strategy activators* (Reigeluth & Stein, 1983) that function as a means of stimulating learners to engage in learning activities of which they are capable, but do not spontaneously apply, or those which they implement unsatisfactorily (Berthold et al., 2007). Empirical evidence shows that prompts can be used as a tool to improve learning (Berthold et al., 2007) and it has been argued that asking trainees self-reflective questions about their learning

strategies stimulates self-regulation (Hübner et al., 2006; Sitzmann et al., 2009; Smith, 1996). In recent work, Sitzmann and colleagues have begun to explore the use of self-regulation prompts as a method of motivating self-regulatory engagement within learner-controlled e-learning (Sitzmann & Ely, 2010; Sitzmann et al., 2009). The results of their investigations suggest that learners in learner-controlled training demonstrate knowledge gains over time when reminded to self-regulate. These results are promising as they indicate that certain design features (i.e., self-regulation prompts) can be incorporated into learner-controlled e-learning that improve learning within these formats. However, they as yet do not address the roll that individual differences may play in their utility.

Individual Differences. The important role of individual differences is evidenced by the emphasis on exploring person attributes during (person) needs analysis prior to training. Person analysis is conducted to answer two questions: 1) who needs training, and 2) what kind of instruction do they need (Goldstein & Ford, 2002)? The premise for person analysis is that by understanding attributes of learners and their unique needs we are better able to provide training programs that target relevant content and employ training methodologies appropriate for the intended training audience. The results of programs targeted to individual needs are improved learning and application of knowledge, skills, and attitudes (KSAs), and, thus, more effective training. However, despite the root intentions of person analysis, Tannenbaum and Yukl (1992) noted that it is more often used to select learners who would do well in training than to design training for the learners. The problem when selecting learners into training on the basis that they are likely to succeed is that many persons who require it are denied the opportunity to improve

their KSAs. The training program will appear to be effective, but at the expense of those who may need it most.

Some learners are, arguably, more trainable than others (Noe, 2008), and there is a substantial body of research aimed at exploring individual differences in trainability. Among these variables are cognitive ability (Blume et al., 2010; Colquitt et al., 2000; Ree & Earles, 1991; Ree, Caretta, & Teachout, 1995), self-efficacy (Sitzmann et al., 2009), personality characteristics such as conscientiousness (Blume et al., 2010; Colquitt, et al., 2000), and goal orientation (Brett & VandeWalle, 1999; Brown, 2001; Ely et al., 2009; Fisher & Ford, 1998; Kozlowski, Gully, Brown, Salas, Smith, & Nason, 2001; Orvis et al., 2009). Several theoretical frameworks and empirical investigations have attempted to explain the contribution of individual differences to training success. For instance, Noe (1986) identified locus of control (i.e., beliefs about one's ability to control the outcomes of events that affect them; Rotter, 1954, 1966), career and job attitudes, and trainee motivation as key determinants of training effectiveness. A few years later, Baldwin and Ford (1988) included trainee characteristics in their model as a general class of variables influential to training transfer (i.e., the application of KSAs learned in training to the job or task). Colquitt, LePine, and Noe (2000) completed a comprehensive meta-analysis on the role of motivation on training outcomes such as skill acquisition and transfer. Most recently, Grossman and Salas (2011) identified cognitive ability, self-efficacy, motivation, and perceived utility of training as having the strongest relationships with transfer.

Despite previous work, Gully and Chen (2010) note that gaps in our understanding of the precise role of individual differences in training still persist and recommended directing additional research focus on how personal characteristics affect training processes and outcomes.

They argued that individual differences are often given secondary attention in training research. It is possible that individual differences are sidelined because state characteristics (e.g., personality) cannot be controlled or regulated. Furthermore, most training research focuses on the relational or predictive relationships rather than a theoretical understanding of how particular individual differences promote learning. As such, there is a lack of focus on the explanatory mechanisms that mediate the effect of individual differences on training outcomes. Finally, most work has not considered how individual differences interact with training design and contextual factors (Gully & Chen, 2010). Yet, as Gully and Chen wrote, “It seems self-evident that individual differences will determine whether trained content is learned, retained, applied, and transferred to the work context” (p. 5). Without a better understanding of the intervening mechanisms and ways in which individual differences interact with training methodologies, it is difficult to know which personal characteristics matter and when they are likely to have influence. Hence, discussion of instructional design features merits contemplation regarding for which persons they are most useful.

Although some research has explored how individual difference characteristics influence whether learners generally benefit from learner-controlled instruction (e.g., Brown, 2001; Schmidt & Ford, 2003; Sitzmann et al., 2009), questions remain regarding for whom the addition of self-regulation prompts are most useful. This is a meaningful distinction because the first vein of research attempts to generalize the effects of individual characteristics on learning within all learner-controlled settings, whereas the second vein seeks to elucidate how specific features of learner-controlled training may be better or worse for certain individuals. Though research on self-regulation prompts in learner controlled e-learning is still somewhat nascent, it is interesting

that more work has not been done that incorporates individual differences since a major point underscoring interest in learner-controlled training is that not all learners are the same and, therefore, not all learners respond to and benefit from instructional methods similarly (Saks & Haccoun, 2008; Snow, 1992). An extension of this logical progression is that individual differences are likely to affect how learners employ learner control options (e.g., Brown, 2001; Kraiger & Jerden, 2007; Orvis et al., 2009; Schmidt & Ford, 2003). As an example, learners with greater cognitive ability more capably manage control options. Consequently, learners do not appear to be universally equipped to effectively regulate their own learning, especially within learner-controlled settings. Similar phenomena are likely to be expected with how learners might react to self-regulation prompts.

Purpose of the Current Study

This dissertation examines how learners behave when presented with self-regulation prompts in e-learning depending on individual difference characteristics. Specifically, I explore the role of goal orientation because of its link to important self-regulatory processes and strategies (Ames, 1992; Chiaburu, Van Dam, & Hutchins, 2010; Church, Elliot, & Gable, 2001; Dweck, 1986; Fisher & Ford, 1998; Ford et al., 1998; Mesmer-Magnus & Viswesvaran, 2007; Schmidt & Ford, 2003; Towler & Dipboye, 2001). The association between goal orientation and learning (Brett & VandeWalle, 1999; Brown, 2001; Ely et al., 2009; Orvis et al., 2009) and self-regulation (Ames, 1992; Church et al., 2001; Chiaburu et al., 2010; Dweck, 1986; Fisher & Ford, 1998; Ford et al., 1998; Towler & Dipboye, 2001) is well known. However, to my knowledge no

one has yet investigated how goal orientation and self-regulation prompts interact to affect self-regulation activity. Nevertheless, the answer to such a question would have implications for the design of e-learning. I expect that individuals with a high prove performance goal orientation will be prevailed upon to self-regulate more when prompted than they otherwise would without cues to self-regulate.

This dissertation contributes to the extant literature in two major ways. First, it contributes additional evidence regarding the potential for using self-regulation prompts within e-learning environments, allowing for the triangulation of evidence of prompts as a training design feature to promote learning. Second, it provides insights regarding what types of learners may best benefit from this feature by testing the relationships between prompts, goal orientation, self-regulation, and learning with what Edwards and Lambert (2007) term a stage 1 moderated mediation model and Hayes (2013) refers to as a conditional process model. Specifically, the current work considers how an aptitude-by-treatment interaction between self-regulation prompts and prove performance goal orientation is mediated by two self-regulatory processes: time-on-task and self-regulatory activity (i.e., the extent to which learners concentrate on learning the training material, remain motivated, and engage in metacognitive activity).

In conducting this research, I directly build on previous investigations exploring how self-regulation prompts in learner controlled e-learning environments can induce better learning via its effect on time on task and self-regulatory activity (Sitzmann & Ely, 2010). My dissertation adds to this research with an investigation of an aptitude-by-treatment interaction between self-regulation prompts and the individual difference variable prove performance goal orientation. As discussed above, Gully and Chen (2010) noted that there is surprisingly little

research that investigates how learner characteristics- such as personality traits, interests, and values- interact with training design features to affect learning. Furthermore, Gully and Chen (2010) suggest that the interaction between learner characteristics and training design features likely operates through intervening mechanisms to change learning outcomes. Thus, my study contributes to the literature base by exploring how performance goal orientation affects the relationship between self-regulation prompts and self-regulatory processes – an under-researched area in general (Gully & Chen, 2010) and one with no extant research with regards to self-regulation prompts. Findings from this dissertation direct recommendations for designing learner-controlled e-learning and have implications for the theory and measurement of learner effort.

In the chapters that follow, I begin by describing each of the main study variables and elaborate on the theoretical drivers that have led me to the specific hypotheses tested in this dissertation. Afterwards, I explain the methods I intend to employ in order to collect and analyze the data needed to adequately test the study hypotheses.

CHAPTER TWO: LITERATURE REVIEW

This dissertation extends recent research studying the effects of prompting self-regulation in learner-controlled computer-based instruction (CBI; Sitzmann et al., 2009; Sitzmann & Ely, 2010). In order to understand the role of training design and individual differences within the context of learner-controlled CBI, I explore the relationships among self-regulation prompts, goal orientation, self-regulatory activity, and learning. Specifically, I examine the mediating effect of self-regulation processes (i.e., self-regulation activity and time on task) between self-regulation prompts and subsequent learning. Further, I investigate how self-regulation prompts and individuals' performance goal orientation interact to constrain or promote the extent to which learners self-regulate during training. A summary of the conceptual and operational definitions of these constructs may be found in Table 1. Figure 1 models the theoretical relationships among these variables. The study hypotheses are summarized in Table 2. In the sections that follow, I detail the specifics of these relationships and explain the theoretical basis supporting my hypotheses regarding these variables.

Table 1. Conceptual and Operational Definitions of Study Variables

<u>Variable</u>	<u>Conceptual Definition</u>	<u>Operational Definition</u>
Self-regulation Prompts	Questions or hints that induce productive learning processes (Berthold et al., 2004, 2007)	Questions learners must ask themselves regarding their engagement in the learning process and readiness for knowledge tests (Sitzmann & Ely, 2010)
Prove Performance Goal Orientation	“The desire to prove one’s competence and to gain favorable judgment about it” (VandeWalle, 1997, p. 1000)	4 item self-report measure utilizing a 6-point Likert scale ranging from 1 = <i>strongly disagree</i> to 6 = <i>strongly agree</i> (VandeWalle, 1997)
Time on Task	The amount of energy learners devote to learning (Fisher & Ford, 1998; Sitzmann & Ely, 2010; Wilhite, 1990)	Time spent reviewing the training materials.
Self-regulatory Activity	“The extent to which learners concentrate on learning the training material, remain motivated, and engage in metacognitive activity” (Sitzmann & Ely, 2010, p. 134).	18-item self-report measure of concentration, motivation, and metacognition utilizing a 6-point Likert scale ranging from 1 = <i>strongly disagree</i> to 5 = <i>strongly agree</i> (Sitzmann & Ely, 2010).
Learning	“A relatively permanent change in knowledge or skill produced by experience” (Weiss, 1990, p. 172)	A multiple-choice assessment of declarative and procedural knowledge administered to participants following each training module.

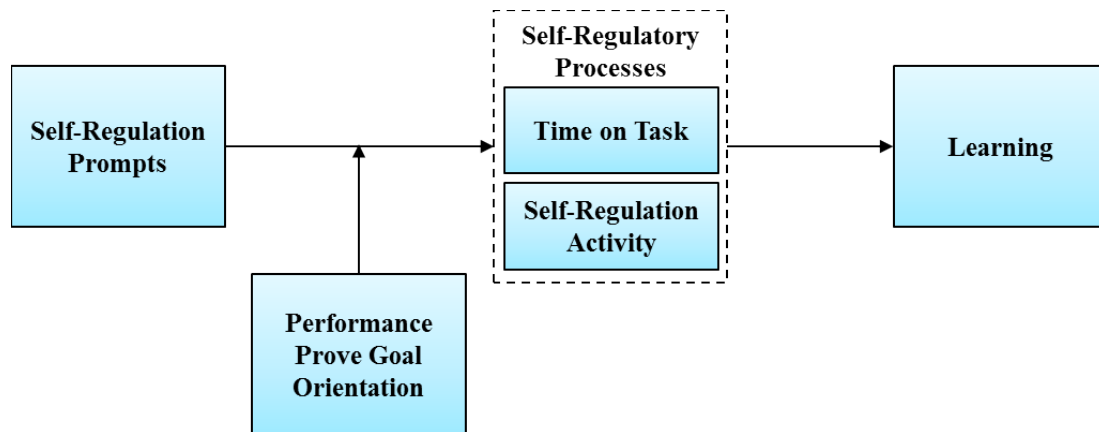


Figure 1. Relationships between Study Variables

Table 2. Summary of Study Hypotheses

H1a	<i>Learners who are prompted to self-regulate will spend more time reviewing training materials.</i>
H1b	<i>Learners who are prompted to self-regulate will engage in more self-regulatory activity than learners who are not prompted to self-regulate.</i>
H2	<i>Learners who are prompted to self-regulate will learn more during training than learners who are not prompted to self-regulate.</i>
H3a	<i>The effect of self-regulation prompts on learning will be mediated by the time learners spend reviewing training materials.</i>
H3b	<i>The effect of self-regulation prompts on learning will be mediated by learners' self-regulatory activity.</i>
H4a	<i>Prove performance goal orientation will moderate the relationship between self-regulation prompts and self-regulation processes such that self-regulation prompts will be more positively related to the time learners spend reviewing training materials when learners are more highly prove performance goal oriented.</i>
H4b	<i>Prove performance goal orientation will moderate the relationship between self-regulation prompts and self-regulatory processes such that self-regulation prompts will be more positively related to self-regulatory activity when learners are more highly prove performance goal oriented.</i>

Self-Regulatory Processes

As discussed above, advocates of prompts interventions argue that prompts increase self-regulatory behavior during training (Hübner et al., 2005; Sitzmann & Ely, 2010; Sitzmann et al., 2006). To understand how this process occurs, previous authors have studied the self-regulatory processes that emerge or are activated as a result of exposure to prompts. *Regulatory processes* are the psychological and behavioral mechanisms learners purposefully engage during training in order to accomplish learning goals. As such, they are the crux of self-regulated learning.

In order to study the effect of self-regulation prompts on self-regulatory processes, Sitzmann and Ely (2010) investigated two self-regulatory processes: general self-regulatory activity and time spent reviewing the training materials. General self-regulatory activity includes the internal processes that learners use to assess progress and adapt learning strategies (metacognition), maintain cognitive focus and attention during training (concentration), and strive to learn the content of the training program (motivation). Time spent reviewing the training materials captures amount of energy that learners expend during training. Time on task and self-regulatory activity are believed to capture unique aspect of self-regulation (e.g., Pintrich, 2000; Sitzmann & Ely, 2011). As a manifestation of internal states, self-regulatory activity encapsulates the psychological aspect of self-regulation whereas time spent reviewing the training material captures the behavioral aspect (Sitzmann & Ely, 2010). Conceptualizing self-regulation processes as having both psychological and behavioral aspects has benefits for understanding the self-regulation construct. Operationalizations of internal (i.e., psychological)

processes and behaviors each have drawbacks, so considering each helps to create a stronger picture of self-regulation.

Internal states, like motivation, can be difficult to measure (Ambrose & Kulik, 1999; Kanfer, 1990) because they are not directly visible (Yeo & Neal, 2004, 2008). They are often measured via self-report, as learners have introspective access to their own internal processing (Humphreys & Revelle, 1984; Locke & Latham, 2004). Learners are uniquely qualified to assess the intensity, or lack thereof, of their internal self-regulatory processes. For instance, Paas, van Merriënboer, and Adam (1994) evaluated the sensitivity, reliability, construct validity, and intrusiveness of subjective measures of *mental effort* (i.e., the cognitive resources devoted to a task; Paas, 1992; Paas, Tuovinen, van Merriënboer, & Darabi, 2005; Paas & van Merriënboer, 1994). Findings from their evaluation indicate that subjective rating scales are sensitive to relatively small differences in the cognitive load resulting from effort and that these measures are valid, reliable, and nonintrusive. However, while subjective self-assessments may be the most direct measure of internal processes available, they are subject to individual idiosyncratic biases. As such, researchers often look for behavioral proxies for internal processing (e.g., time spent reviewing training materials).

Operationalizing self-regulation as time on task is beneficial in that it provides objective quantification of behavior expected from individuals determined to perform well on a task. Unfortunately, it can be an incomplete or contaminated estimation of self-regulation as it does not directly capture the internal components (e.g., attention, motivation, metacognition). For instance, a measure of time cannot account for periods during which learners appear to be engaged in the task but whose thoughts are actually focused elsewhere. As such, measures

operationalizing effort as time duration are easily contaminated, especially when measured via internal e-learning systems incapable of separating time spent on the task from time spent attending to other activities while leaving the learning system open. Therefore, measuring both internal and observable aspects of self-regulation provide a more complete understanding of the construct.

Attention is a limited capacity resource that may be allocated to on-task, off-task, or self-regulatory activities (Kanfer & Ackerman, 1989). Different task demands are always in competition for these resources. Conflicting responsibilities are apt to reduce learners' commitment to training, causing them to consciously or unconsciously seek shortcuts to learning that may impede knowledge gains. However, Winne (1995) noted that learners are disposed to use more challenging study strategies when they receive indication that the strategies are helpful. Similarly, prompting self-regulation during instruction may signal to learners the importance and utility of self-regulation and encourage them to allocate more of their cognitive resources to training materials. Prompts may also provide learners with hints regarding what strategies useful for learning and inspire them to commit additional effort to implementing these strategies.

Resource allocation theory suggests that learners regulate the amount of cognitive resources allocated to a task in order to maintain performance (Kanfer & Ackerman, 1989). Prompts, by design, bring learners' attention to learning, and thus, require them to reflect on their achievement progress. In so doing, learners must determine whether they are meeting, exceeding, or falling short of their performance expectations. Control theory suggests that when faced with a discrepancy between current and desired performance, learners examine the probability of reaching their performance goal should they increase effort (Carver & Scheier, 1990, 1998,

2000). At this juncture, learners must decide whether they should 1) extend more effort in the pursuit of desired performance, 2) continue on the task but mentally disengage, or 3) completely discontinue task participation (Kanfer & Ackerman, 1989). According to resource allocation theory, when learners perceive that their performance can be improved by dedicating greater effort to a task, they will reallocate resources to that task. Prompts are expected to prevent learners from choosing to disengage or withdraw participation by promoting learners' perceptions that learning goals are attainable and stimulating them to engage in additional learning activities. Recipients of self-regulatory prompts will spend additional time and commit greater cognitive resources to enacting learning strategies in the pursuit of desired performance.

Thus, I hypothesize:

Hypothesis 1a: *Learners who are prompted to self-regulate will spend more time reviewing training material.*

Hypothesis 1b: *Learners who are prompted to self-regulate will engage in more self-regulatory activity than learners who are not prompted to self-regulate.*

Learning

Learning is defined as “a relatively permanent change in knowledge or skill produced by experience” (Weiss, 1990, p. 172). As an outcome of training, learning is of particular interest in organizational settings, where expertise is explicitly linked to performance (Goldstein & Ford, 2002). Ultimately, organizations need a workforce of employees capable of performing their jobs effectively and efficiently. Learning from formal training or informal instruction is a compulsory

stepping stone in the application of the knowledge, skills, and attitudes (KSAs) necessary for adequate job performance (Baldwin & Ford, 1988). Thus, training programs must be able to instill in learners permanent changes in job-relevant KSAs. Because learning is often the primary goal of training, it is also one outcome against which training is evaluated (Bloom, 1956; Kirkpatrick, 1959, 1996; Kraiger, Ford, & Salas, 1993).

A rich science dedicated to optimizing learning has emerged (Salas & Cannon-Bowers, 2001; Salas, Tannenbaum, Kraiger, & Smith-Jentsch, 2012). This science explores individual difference characteristics (Chen, Gully, Whiteman, & Kilcullen, 2000; Gully & Chen, 2010), training design (Bell & Kozlowski, 2010; Arthur, Bennett, Edens, & Bell, 2003), and workplace characteristics (e.g., Blume et al., 2010; Mathieu & Tesluk, 2010) that affect training outcomes such as learning and transfer of KSAs to the job context. Self-regulation prompts are one design feature shown to positively affect performance achievement (i.e., learning) in training (Berthold et al., 2004, 2007; Hüber et al., 2006; Kauffman, 2004; Sitzmann et al., 2009; Sitzmann & Ely, 2010). Cognitive load theory (CLT) can be used to explain how prompts are expected to influence learning.

Cognitive Load Theory. Based on theories of human cognitive architecture (Kirschner, 2002; Cierniak, Scheiter, & Gerjets, 2008; Sweller et al., 1998), CLT submits that working memory is limited in its storage capacity and ability to process new information (Baddeley, 1992; G. A. Miller, 1956). Working memory can be equated with consciousness in that humans are aware of and only capable of monitoring the contents of working memory; all other cognitive processes are unknown unless and until they can be brought into working memory (Sweller et al., 1998). Alternatively, long-term memory is believed to be virtually limitless in the amount of

information that can be stored (Krischner, 2002). Before information can be coded in long-term memory, where it is ultimately stored (Sweller et al., 1998), it must be processed in working memory (Gerjets & Scheiter, 2003). Working memory is, therefore, the conduit through which learning occurs; yet because of its limited capacity it is considered a bottleneck to learning (Granger, 2012). The load imposed on working memory depends on the number of items to be learned that must be processed simultaneously (Sweller et al., 1998). CLT distinguishes between three sources of cognitive load that place demands on learners' limited working memory resources: intrinsic, extrinsic, and germane cognitive load (Sweller, 2005). Each of these sources of cognitive load, together and in isolation, affects the mental workload experienced by learners during training.

Intrinsic cognitive load. According to CLT, *intrinsic cognitive load* stems from the nature of the training material itself and cannot be altered (Sweller, 2010; Sweller et al., 1998). Intrinsic cognitive load is determined by the interactivity of the learning elements and the expertise of the individual learner (Sweller et al., 1998). Information varies on a continuum of low to high interactivity (Paas et al., 2003). Information elements low on interactivity may be processed and understood in isolation. Elements high on interactivity, however, must be processed simultaneously within working memory. Therefore, the greater the interactivity between elements to be learned, the greater the cognitive load experienced by the learner. However, the expertise of the learner may lessen cognitive load experienced while handling highly interactive elements through the construction of *schemas*. Schemas are cognitive constructs that incorporate multiple informational elements into a single element with a specific function (Paas et al., 2003). As learners gain expertise, they begin to cognitively organize and

group highly interactive elements, resulting in a schema (Ayres & van Gog, 2009). As familiarity with the material increases and expertise is developed, learners no longer need to process the individual elements independently. Instead, they bring schemas consisting of a number of lower-level elements and their interdependent relationships into working memory, permitting simultaneous attention to more information than was previously possible. In essence, the same material can be processed either as many distinct pieces of information, as done by novice learners, or as a few chunks of information, characteristic of experienced learners (Chi, Glaser, & Rees, 1982; van Merriënboer, Kester, & Paas, 2006).

Extraneous cognitive load. Also referred to as *ineffective cognitive load*, *extraneous cognitive load* is the load imposed on learners by the manner in which information is presented (Paas et al., 2003; Sweller, 2010; Sweller et al., 1998). While CLT suggests that instructors do not have any control over intrinsic cognitive load, its tenets denote that instructional design influences the extraneous cognitive load experienced by learners (Kirschner, 2002). Design features, such as degree of learner control, influence cognitive load and can reduce available working memory resources (Bannert, 2002). Work in CLT suggests that providing high degrees of learner control during training may increase levels of extraneous cognitive load (Scheiter & Gerjets, 2007). Indeed, the detrimental effects of learner control on learning demonstrated by some research findings (e.g., Bell & Kozlowski, 2002; Brown, 2001; Kraiger, 2008a, 2008b) may be the result of unduly high levels of extraneous cognitive load (Granger, 2012; Granger & Levine, 2010). However, extraneous cognitive load may only be a problem when training material is complex. When training material is low on interactivity, learner control does not appear to be any less effective than program controlled training (Granger, 2012). It is likely that

training of complex material in a learner controlled environment easily overloads working memory, as both intrinsic and extrinsic cognitive load are high in these situations. Theory and evidence suggests that intrinsic and extrinsic cognitive load are additive in that, together, they place greater demands on working memory than either does in isolation (Paas et al., 2003; Sweller, 2010; Sweller et al., 1998). As a result, when high levels of both types of cognitive load occur in tandem, working memory may be exceeded and performance suffers. When either intrinsic or extraneous load is reduced, however, some working memory resources are freed that may be reallocated to learning strategies (i.e., germane cognitive load, discussed next). When training material itself is simple, intrinsic cognitive load is low and learners are better equipped to handle the extraneous demands imposed by the training design in addition to managing their learning (Granger, 2012). As a result, instructional designs intended to reduce cognitive load are most effective when element interactivity is high (Paas et al., 2003).

Germane cognitive load. Proponents of CLT point towards a third source of cognitive load known as *germane cognitive load*, or *effective cognitive load*. Unlike intrinsic and extrinsic sources of cognitive load, which consume cognitive resources but do not assist in encoding information in long-term memory, germane cognitive load enhances learning. Instead of devoting working memory to ineffective learning processes (e.g., information search), which occurs when extraneous cognitive load is high, germane cognitive load results from dedicating resources to schema acquisition and automation (Paas et al., 2003; Sweller, 2010). Like extraneous cognitive load, germane cognitive load may be impacted by instructional design. The manner in which information is presented to learners and the instructional activities required of learners are factors that influence germane cognitive load. The basic assumption is that an

instructional design that results in unused working memory resources because of a low intrinsic load imposed by the materials and/or low extraneous load due to effectively designed instructional procedures may be further enhanced by redirecting learner's available resources to conscious cognitive processing of information and construction of schemas (Sweller et al., 1998). Learners' attention must be withdrawn from processes not relevant to learning and directed toward processes relevant to learning, particularly those involved in construction and automation of schemas within long-term memory (van Merriënboer, 1997). This is the goal of self-regulatory prompts: to draw learners' attention to the learning material and encourage them to apply unused cognitive resources to regulating learning and assimilation of organized cognitive representations of training information. Of course, the additive effects of germane, extraneous, and intrinsic cognitive load must remain within the limits of working memory in order for optimal learning. However, when working memory resources are available, prompting is expected to encourage learners to apply these unused resources towards self-regulatory activities (Berthold et al., 2007; Sitzmann et al., 2009; Sitzmann & Ely 2010) that are positively related to learning during training (Sitzmann & Ely, 2011; Zimmerman & Martinez-Pons, 1986, 1988). It is anticipated that learners will dedicate more time and mental effort whilst they seek to create schemas of the learning materials. It is through this enhanced effort that learning is expected to occur (Fisher & Ford, 1998; Sitzmann & Ely, 2010, 2011; Yeo & Neal, 2004), leading me to hypothesize:

Hypothesis 2: *Learners who are prompted to self-regulate will learn more during training than learners who are not prompted to self-regulate.*

Hypothesis 3a: *The effect of self-regulation prompts on learning will be mediated by the time spend reviewing the training materials.*

Hypothesis 3b: *The effect of self-regulation prompts on learning will be mediated by learners' self-regulatory activity.*

Goal Orientation

Goal orientation refers to how individuals approach, interpret, and respond to achievement situations (Brett & VandeWalle, 1999; Dweck & Leggett, 1988; Elliot & Harackiewicz, 1996). Dweck (1986, 1989) described two major classes of achievement goal orientations: learning goal orientation and performance goal orientation. Learning and performance orientations are characterized by different motivations for engaging in learning and different philosophies regarding success (Ames, 1992). A learning orientation focuses on the development of competence and task mastery. Performance orientation, on the other hand, is centered on a desire to demonstrate one's ability in relation to others (Kozlowski & Bell, 2006).

Underlying the difference between learning orientation and performance orientation are beliefs about effort and ability. Learning-oriented and performance-oriented individuals hold different implicit beliefs about the malleability of personal characteristics, especially those related to ability (Dweck, 1986). Learning-oriented individuals tend to identify with the tenants of incremental theory; that is, they believe ability is changeable and can be developed through conscious effort and experience. Alternatively, performance-oriented individuals tend to hold beliefs about personal attributes that are founded in entity theory; that is, they believe ability is a fixed, uncontrollable and unchangeable trait. As a result of these differing views, goal orientation influences how individuals judge the exertion of effort (Ames, 1992; Dweck & Legget, 1988).

Learning-oriented individuals view effort as an instrumental strategy for developing the ability needed for maximal performance. In other words, individuals with a learning orientation believe that greater effort will lead to greater success. Alternatively, performance-oriented individuals associate higher effort with lower ability, which can be damaging to self-image. Consequently, performance-oriented learners may report decreased interest in the task, make negative ability attributions, and ultimately withdraw from the task.

The two major classes of goal orientations are associated with distinct patterns of self-regulation (Dweck, 1986; Kozlowski & Bell, 2006) and have subsequent effects on cognitive performance (Dweck, 1986). The adaptive pattern is associated with learning-oriented individuals and is characterized by challenge-seeking behavior and persistence in response to obstacles. Learning-oriented individuals carefully monitor their learning progress and respond to obstacles by increasing effort or analyzing and changing their learning strategy (Dierdorff & Ellington, 2012; Ford et al., 1998; Metcalfe & Shimamura, 1994; Nelson & Narens, 1990; Schmidt & Ford, 2003), often culminating in improved performance. The maladaptive pattern is associated with performance-oriented individuals and is characterized by challenge-avoidance and low persistence when experiencing obstacles (Ames, 1992; Church et al., 2001; Dweck, 1986; R. B. Miller, Behrens, & Greene, 1993, which promotes defensive tactics that limit challenge-seeking activity (Dweck, 1986). Performance orientation requires individuals' perceptions of their abilities be high and remain high during challenging tasks (Dweck, 1986). Unfortunately, complex tasks challenge individuals' perceptions of their ability, and performance-oriented individuals have difficulty sustaining motivation as failure is attributed to a lack of ability. Therefore, performance-oriented individuals may try to avoid situations in

which they do not excel and instead seek opportunities to showcase their ability (Ames, 1992; Duda & Nicholls, 1992; Elliot & Harackiewicz, 1996; Middleton & Midgley, 1997).

Goal orientation in learning situations is influenced by both dispositional and situational factors that operate independently (Archer, 1994; Boyle & Klimoski, 1995; Chen et al., 2000; Kozlowski et al., 2001). Although the dispositional aspect is relatively stable over time, situational cues can cause individuals to adopt a different orientation or weaken their typical response pattern under achievement conditions (Button, Mathieu, & Zajac, 1996). This has led researchers to develop and implement a variety of interventions intended to induce achievement orientations, generally manipulating cues to frame training (Ames, 1992; Archer, 1994; Frese, Albrecht, Altmann, Lang, Papstein, Peyerl, et al., 1988; Ivancic & Hesketh, 1995/1996; Keith & Frese, 2005; Kozlowski et al., 2001; Kozlowski, Toney, Mullins, Weissbein, Brown, & Bell, 2001; Martocchio, 1992, 1994; Meece, 1994; Wood & Bandura, 1989). Empirical evidence generally suggests that a learning frame promotes an adaptive pattern of self-regulation, whereas a performance frame supports a more negative self-regulatory response pattern (see meta-analyses by Rawsthorne & Elliot, 1999; Utman, 1997). Following in the tradition of these interventions, prompting self-regulation encourages all learners to engage in self-regulatory activities.

Since learning-oriented individuals already naturally tend to adopt adaptive response patterns in achievement situations which manifests in part as the exertion of effort, it is expected that prompting self-regulation in training will most benefit those learners who are predisposed towards a performance orientation. However, performance goal orientation captures both a desire to avoid others' negative judgments as well as the desire to gain favorable attributions about

one's ability (Heyman & Dweck, 1992). Some authors have argued that the desires to gain approval and avoid disapproval represent different goals (Nicholls, 1984; VandeWalle, 1997). Thus, VandeWalle (1997) distinguishes between two types of performance goal orientations, which he labels, *prove performance* and *avoid performance* goal orientation. Prove performance goal orientation is the "desire to prove one's competence and to gain favorable judgments about it" (VandeWalle, 1997, p. 1000). Avoid performance goal orientation, on the other hand, is the "desire to avoid the disproving of one's competence and to avoid negative judgments about it" (VandeWalle, 1997, p. 1000). These differing performance goal orientations will likely disparately influence how learners respond to self-regulation prompts in training situations.

VandeWalle's (1997) two types of performance orientation overlap in that they both describe individuals who look to external referents for approval or disapproval. Neither prove performance- nor avoid performance-oriented learners seek to engage in activities which they know to be challenging; instead, learners of both types would prefer to avoid difficult activities altogether, and only approach activities at which they know they are competent. However, prove performance- and avoid performance-oriented individuals differ in how they are expected to respond to situations in which they know they are being externally evaluated. Avoid performance-oriented learners will not expend any effort as a mechanism to protect their self-image. Rather than risk looking incompetent, learners higher on avoid performance goal orientation will shut down, justifying their behavior by arguing that no one can really know of what they are capable since they did not try. Through non-action, avoid performance-oriented individuals believe they can evade failure. Alternatively, learners higher on prove-performance

goal orientation will want to demonstrate their abilities and will, therefore, approach evaluative situations.

In view of the fact that they are expected to shun situations in which they may be evaluated, I do not anticipate that self-regulation prompts will affect avoid performance-oriented learners' effort during training. If anything, I would suspect that prompts could have a negative effect on these individuals who may actually retreat even more from the task as a result of being reminded that they will be evaluated. Therefore, this dissertation explores how learners with a prove performance goal orientation react to self-regulation prompts. Specifically, I believe that since prompts serve as reminders that learning will be evaluated, prove performance-oriented individuals will exert more effort when prompted than they would otherwise. Thus, I hypothesize,

Hypothesis 4a: *Prove performance goal orientation will moderate the relationship between self-regulation prompts and self-regulation processes such that self-regulation prompts will be more positively related to the time learners spend reviewing training materials when learners are more highly prove performance goal oriented.*

Hypothesis 4b: *Prove performance goal orientation will moderate the relationship between self-regulation prompts and self-regulation processes such that self-regulation prompts will be more positively related to self-regulatory activity when learners are more highly prove performance goal oriented*

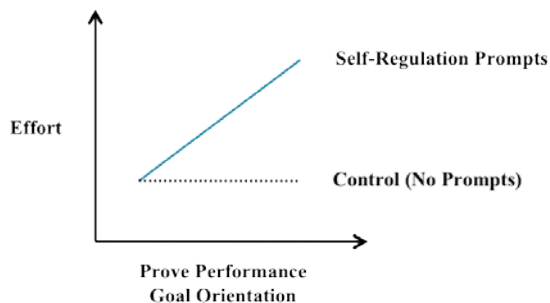


Figure 2. Hypothesized Interaction between Self-Regulation Prompts, Prove Performance Goal Orientation, and Effort

Control Variables

Cognitive ability. *Cognitive ability*, or *general mental ability*, describes individuals' aptitude to "understand complex ideas, to adapt effectively to the environment, to learn from experience, to engage in various forms of reasoning, [and] to overcome obstacles by taking thought" (Neisser et al., 1996, p. 77). It is well established that cognitive ability is strongly related to academic performance (Kuncel, Hezlett, & Ones, 2001), job performance (Bertua, Anderson, & Salgado, 2005; Hunter, 1986; Neisser, et al., 1996; G. Park, Lubinski, & Benbow, 2007; Schmidt & Hunter, 2004), career success (Judge, Higgins, Thoresen, & Barrick, 1999; Schmidt & Hunter, 2004), and training learning outcomes (Bertua et al., 2005; Ree et al., 1995; Ree & Earles, 1991) and so will be used as a control variable in the analysis of relationships involving learning.

CHAPTER THREE: METHOD

Needs Analysis

The training program used in this dissertation taught participants Microsoft Excel 2013 knowledge and skills. In order to determine the particular content appropriate for Microsoft Excel training, a needs analysis was conducted using a sample of undergraduate students at a large Southeastern university. Data were collected from 89 participants via an online survey. The survey consisted of three major sections: demographics and familiarity with and use of Microsoft Excel, a 47-item multiple choice declarative and procedural knowledge test of Microsoft Excel features, and VandeWalle's (1997) 13-item goal orientation measure. The goal orientation measure was anchored on a 1 to 5 Likert scale where *1 = strongly disagree* and *5 = strongly agree*. Familiarity with Microsoft Excel and the declarative knowledge test were included as mechanisms for assessing the average level of competence with Microsoft Excel within the targeted population. The purpose of including these items was to use the findings to ensure that the proposed training task is appropriate for the participants. Microsoft Excel training that is either too advanced or simple will fail to induce learning, restricting the variance and making it impossible to detect any true effect. Goal orientation was measured for two purposes. First, goal orientation was measured in order to determine whether prove performance oriented individuals would be inclined to sign up for an investigational study given their natural tendency to avoid situations in which they could fail to demonstrate aptitude. Second, I wanted to estimate the distribution of prove performance goal oriented individuals within the targeted population. In

order to test hypothesis 4, it is desirable for the sample pool to include participants scoring extremely high and extremely low on prove performance goal orientation. A sample pool distribution without these extremes is range restricted and severely limits the study’s ability to appropriately test hypothesis 4.

Results of the needs analysis indicate that undergraduates’ baseline knowledge of Microsoft Excel is minimal. Table 3 presents the overall and subsection results. On average, participants only answered 25.02% ($M = 8.45$, $SD = 6.21$) of the knowledge questions correctly. Specifically, participants correctly responded to 36.6% ($M = 4.40$, $SD = 2.84$) of the 12 items assessing knowledge of Microsoft Excel Basics (e.g., formatting), 13.6% ($M = 1.63$, $SD = 1.72$) of the 12 Data Analysis (e.g. sorting data, auto calculations) items, 14.5% ($M = 1.59$, $SD = 1.91$) of the 11 Graphs and Charts (e.g., creating histograms and pie charts) items, and 7.0% ($M = 0.84$, $SD = 1.19$) of the 12 Microsoft Excel Advanced Functions (e.g., macros) items. Only one respondent scored above a 62% on the test overall. Furthermore, 84 (97.7%) respondents scored below a 76% on the Microsoft Excel Basics questions. No one scored above a 73% on any of the other subsections of the test (i.e., Data Analysis, Graphs and Charts, and Advanced Functions). These results lead me to believe that the proposed content of the training task is appropriate. It seems that most undergraduates could benefit from participation in a basic Microsoft Excel training program.

Table 3. Average Overall and Subsection Scores on the Needs Analysis Declarative Knowledge Test

	Overall Score	Basics	Data Analysis	Graphs and Charts	Advanced Functions
Percentage	23.940%	36.150%	13.730%	14.970%	7.350%
Raw <i>M</i>	8.515	4.338	1.647	1.647	0.882
Raw <i>SD</i>	6.149	2.832	1.691	1.922	1.264

Analysis of prove performance goal orientation distribution indicates that prove performance oriented individuals are willing to participate in an investigational study that will assess their achievement on a knowledge test. The distribution is near normal ($M = 3.54$; $Mode = 3.00$); it is neither significantly skewed ($Skew = -.464$, $SE = .260$) nor significantly kurtoic ($Kurtosis = .854$, $SE = .514$). Although the distribution shows that the sample pool includes individuals scoring on the high and low extremes of the prove performance goal orientation measure, it is important to note that, as is typical of a normal distribution, there are far fewer individuals in the extremes than there are in the center. Indeed, only 25% fall below a middle score of 3.00 whereas the top 25% score above a 4.00. Fifty percent of the distribution falls between 3.00 and 4.00 on a 5 point scale. The clumping of majority of scores in the center of the prove performance goal orientation scale could be problematic for testing hypothesis 4 unless careful procedures are taken during data collection to ensure that each study condition (control vs. treatment) are carefully balanced to ensure that each represents a range of prove performance goal oriented participants. Unbalanced conditions will reduce power, obscuring the ability to detect true effects and increasing the risk of a Type II error.

In sum, the needs analysis provides evidence that training content focused on Microsoft Excel basics is appropriate for the proposed research. Moreover, the needs analysis indicates that care must be taken to ensure participants in the dissertation study are evenly assigned to conditions.

Participants

Participants were 159 adult (18 years of age or older) volunteers who received free Microsoft Excel training. They were recruited online and in psychology classes at four universities on the East Coast. As compensation, participants received either research credit or the opportunity to access the learning materials again in the future. The majority of participants were undergraduate students (93.1%), whereas 6.3% were college graduates, and 0.6% did not attend college. Of those who were undergraduate students, 32.7% were freshmen, 13.2% were sophomores, 20.1% were juniors, and 27.0% were seniors. Most participants were Caucasian (53.5%), followed by African American (14.5%), Latino (16.4%), Asian (3.8%), Indian (2.5%), Middle Eastern (0.6%), Pacific Islander (0.6%), and Native American (0.6%). Additionally, 7.5% of participants identified their ethnicity as 'other', usually indicating a mixed heritage. The average age of participants was 21.44 years and 67.90% were female. Table 4 presents the demographic information for the participants as a percentage of the sample.

Table 4. Participant Demographics as a Percentage of the Sample

Variable	<i>n</i>	%
Academic year		
Freshman	52	32.7
Sophomore	21	13.2
Junior	32	20.1
Senior	43	27.0
Graduate	10	6.3
No College	1	0.6
Ethnicity		
Caucasian	85	53.5
African American	23	14.5
Latino/Latina	26	16.4
Asian	6	3.8
Indian	4	2.5
Middle Easterner	1	0.6
Pacific Islander	1	0.6
Native American	1	0.6
Other	12	7.5
Sex		
Female	108	67.9
Male	51	32.1

Power analysis. The sample size needed for this dissertation to have sufficient power to adequately test the stage 1 moderated mediation (Edwards & Lambert, 2007) model using path analytic procedures was estimated a priori. Though it is difficult to adequately estimate a sample size a priori for complex statistical procedures, generally speaking, larger is better. Two rules of thumb provided guidance for estimating sample size for the present study. The first is sample size conventions for structural equation modeling (SEM). SEM is a large-sample, path analysis procedure capable of testing an entire model at one time. Sample size guidelines for SEM are typically based on an N -to- k ratio of at least 10:1 (Nunnally, 1967), where N = sample size and k = the number of manifest variables in the statistical model. However, a 10:1 ratio is considered to be a minimal estimate of sample size whereas a ratio of 35:1 is more ideal. For this study, a 35:1

ratio renders an estimated sample size of 210 ($k = 6$, 4 manifest variables [experimental condition, prove performance goal orientation, time on task, and self-regulation activity] and 1 control variable [cognitive ability]).

A second approach to estimating sample size is to consider guidelines for multilevel linear modeling (MLM), another large-sample, regression-based procedure. A sample size of at least 60 is recommended for statistical models including five or fewer parameters (Eliason, 1993; Tabachnick and Fidel, 2007). I followed the steps described by Edwards and Lambert (2007) to define the equations for testing a stage 1 moderated mediation model.

Hypothesis 1a states that learners who are prompted to self-regulate will spend more time reviewing training material and Hypothesis 1b states that learners who are prompted to self-regulate will engage in more self-regulatory activity than learners who are not prompted to self-regulate. Hypotheses 1a and 1b were modeled using the regression equations:

$$\text{Time on Task (TT)} = a_0 + a_1\text{Prompts} + a_2\text{CA} + e_{TT}$$

$$\text{Self-regulation Activity (SA)} = b_0 + b_1\text{Prompts} + b_2\text{CA} + e_{SA}$$

where a_0 and b_0 represent the intercepts of the equations for time on task (TT) and self-regulation activity (SA), respectively, a_1 and b_1 represent the slope of Prompts, a_2 and b_2 represent the slopes of cognitive ability (CA), and e_{TT} and e_{SA} represent the residual error terms for each equation.

Hypothesis 2 states that learners who are prompted to self-regulate will learn more than learners who are not prompted to self-regulate. This hypothesis was tested with the following regression equation:

$$\text{Learning (Lrng)} = c_0 + c_1\text{Prompts} + c_2\text{TT} + c_3\text{SA} + c_4\text{CA} + e_{Lrng}$$

where c_0 represents the intercept, c_1 , c_2 , c_3 , and c_4 , represent the slopes of prompts, TT, SA, and CA, respectively, and e_{Lrng} represents the residual error.

Hypothesis 3a states that the effect of self-regulation prompts on learning will be mediated by the time learners spend reviewing the training material and Hypothesis 3b states that the effect of self-regulation prompts on learning will be mediated by learners' self-regulatory activity. The statistical model for testing these hypotheses is defined by combining the equations for time on task, self-regulation activity, and learning as follows:

$$Learning (Lrng) = c_0 + c_1Prompts + c_2(a_0 + a_1Prompts + e_{TT}) + c_3(b_0 + b_1Prompts + e_{SA}) + c_4CA + e_{Lrng}$$

which reduces to:

$$Learning = c_0 + a_0c_2 + b_0c_3 + (c_1 + a_1c_2 + b_1c_3)Prompts + c_4CA + e_{Lrng} + c_2e_{TT} + c_3e_{SA}$$

Hypothesis 4a states that prove performance goal orientation will moderate the relationship between self-regulation prompts and effort such that self-regulation prompts will be more positively related to the time learners spend reviewing training materials when learners are more highly prove performance goal oriented. Similarly, Hypothesis 4b states that prove performance goal orientation will moderate the relationship between self-regulation prompts and effort such that self-regulation prompts will be more positively related to self-regulatory activity when learners are more highly prove performance goal oriented. I used Edwards and Lambert's (2007) process for building the first stage moderated mediation (i.e., conditional process; Hayes, 2007) model. I began by defining the moderation models for time on task, self-regulation activity, and learning.

$$Time\ on\ Task\ (TT) = a_0 + a_1Prompts + a_2PPGO + a_3Prompts \times PPGO + a_4CA + e_{TT}$$

$$\text{Self-regulation Activity (SA)} = b_0 + b_1\text{Prompts} + b_2\text{PPGO} + b_3\text{Prompts}\times\text{PPGO} + b_4\text{CA} + e_{SA}$$

$$\text{Learning} = c_0 + c_1\text{Prompts} + c_2\text{PPGO} + c_3\text{Prompts}\times\text{PPGO} + c_4\text{TT} + c_5\text{SA} + c_6\text{CA} + e_{Lrn}$$

where a_3 , b_3 , and c_3 are now the slopes for the interaction term Prompts×PPGO in each equation and the remaining nomenclature is consistent with the system used above. Substituting the equations for time on task and self-regulation activity into learning generates the first-stage moderation mediation model:

$$\text{Learning} = c_0 + c_1\text{Prompts} + c_2\text{PPGO} + c_3\text{Prompts}\times\text{PPGO} + c_4(a_0 + a_1\text{Prompts} + a_2\text{PPGO} + a_3\text{Prompts}\times\text{PPGO} + e_{TT}) + c_5(b_0 + b_1\text{Prompts} + b_2\text{PPGO} + b_3\text{Prompts}\times\text{PPGO} + e_{SA}) + c_6\text{CA} + e_{Lrn}$$

which reduces to:

$$\text{Learning} = c_0 + a_0c_4 + b_0c_5 + (c_1 + a_1c_4 + b_1c_5)\text{Prompts} + (c_2 + a_2c_4 + b_2c_5)\text{PPGO} + (c_3 + a_3c_4 + b_3c_5)\text{Prompts}\times\text{PPGO} + c_6\text{CA} + c_4e_{TT} + c_5e_{SA} + e_{Lrn}$$

Extrapolating the rule of thumb for estimating sample size in MLM to the 16-parameter statistical model above recommends a sample size of approximately 180.

According to the above estimates, with a sample size of 159 the current study may be slightly underpowered by SEM and MLM standards. However, it does meet the power standards recommended by Tabachnick and Fidel (2007) for testing hypotheses using linear regression. They recommend an N to k ratio of 20:1. The current study surpasses the minimum needed sample of 120 estimated using Tabachnick and Fidel's (2007) recommendation. Furthermore, the ordinary least squares (OLS) regression approach used in this study to test the hypotheses is slightly more robust against smaller samples than SEM methods. Indeed, Hayes (2013) suggests that coefficients estimated using an SEM program are more likely to be slightly erroneous in smaller samples since SEM programs usually derive coefficients from the normal distribution.

The t distribution utilized in OLS regression procedures, on the other hand, is more appropriate for the derivation of coefficients in smaller sample sizes.

Experimental Design and Procedure

This study used a between groups design to test the research hypotheses. The study was hosted online by Qualtrics, a research software company based in Provo, Utah. Participants accessed the study via a website link to the study materials where they provided consent and completed pre-training demographics measures, including cognitive ability, goal orientation, and existing knowledge of Microsoft Excel. Participants were also told that they would be required to e-mail the investigator their scores on the post-test. The purpose of this minor deception was to create an achievement environment that would stimulate learners' goal orientation.

Following the pre-training measures, participants were randomly assigned to either the experimental or control conditions by Qualtrics. Participants in each group received Microsoft Excel training developed by the Goodwill Community Foundation (GCF, 2014). Training covered a variety of Excel features, including basics (e.g., saving and formatting), formulas and functions, tables and charts, PivotTables, and goal seek. Participants in the experimental condition viewed the following message at the beginning of training:

Research has shown that asking yourself questions about whether you are concentrating on learning the training material will increase how much you learn during training. The training program will periodically ask you questions about how you are directing your mental resources and whether you are making progress toward learning the training material. Honestly answer these questions and use your responses to direct your learning (Sitzmann & Ely, 2010, p. 136).

They were then asked three prompts questions per module, for a total of 12 prompts (Appendix A) intended to encourage self-regulation. They responded to the questions using a 5-point Likert scale (1 = *not at all* to 5 = *definitely*). The purpose of having learners respond to the questions was to ensure they thought about the questions. An example question is, “Am I focusing my mental effort on the training material?” An answer of *definitely* indicates that the learner focused on the training material; alternatively, an answer of *not at all* suggests that the learner is not thinking about the training material and that they should refocus their cognitive resources on learning. Regardless of how learners respond, the question prompts learners to evaluate their current level of concentration. Participants in the control condition did not receive any questions during training. However, in order to prevent confounding from the additional time participants in the experimental condition spent responding to the prompts during training, the participants in the control group answered 12 questions on technology readiness after finishing the post-test (see Appendix B).

During training, participants were given control over both scheduling and instructional elements. Since the study was hosted online, participants were able to access the study whenever and wherever they desired (i.e., scheduling control). In addition to scheduling control, participants were provided control over delivery, sequence, content, and pace of instruction. Participants could choose between reading text-based instruction that included screen shots demonstrating step-by-step how to perform the functions being trained and/or watching videos that actively explained and demonstrated the same functions in real-time. Throughout training, participants had access to a navigation window that permitted them to view all of the topics in the training program in a table of contents format. Participants could control the order (i.e.,

sequence) in which they received the training content by selecting topics of interest from the table of contents' navigation pane at any time. When they selected a new topic, they were immediately taken to the related materials. Furthermore, participants were able to skip any content they did not wish to learn, providing control over not only the sequence but the content of the training itself. Participants could exit the training and proceed to the post-test at any time, whether they had viewed all, none, or part of the content. Additionally, participants could choose the length of time that they decided to spend on materials (i.e., pacing). They could choose to spend more time on certain topics while skimming or skipping others, and they decided when they wanted to move on to new topics or the post-test. Once they opted to enter the post-test participants could not go back to the training materials. They received a message to confirm that they were ready to complete the training before they were moved into the post-test.

Following training, all participants completed the post-test and were debriefed regarding the study manipulation and deception. In addition, participants in the control condition also completed the technology readiness items.

Measures

Prove performance goal orientation. Prove performance goal orientation was measured using the 4-item scale developed by VandeWalle (1997). Participants responded to the items using a 6-point Likert scale ranging from 1 = *strongly disagree* to 6 = *strongly agree* so that a higher score indicates stronger goal orientation. A sample item is, "I prefer to work on projects

where I can prove my ability to others.” Cronbach’s alpha (α ; i.e., a measure of internal reliability of the scale) was 0.73.

Learning and knowledge. Previous knowledge and learning were measured using 20 items adapted from the GCF Excel 2013 Quiz (GCF, 2014; see Appendix D for the complete scale). The content and language of the items matched directly onto the language used in the training. To make the test slightly more challenging, some items were modified so that the correct items were not as obvious when compared to distractor items. For instance, a fourth distractor item was added to the question, “If you want to display a data in a certain way (such as Friday, March 1, 2013), you can adjust the ___”, which originally only had three response options. The average pre- and post-test scores were 7.81 and 11.99, respectively.

The knowledge test was administered both pre- and post-training. The pre-training assessment provided a measure of participants’ baseline Microsoft Excel knowledge. The post-training assessment was used to indicate knowledge after participating in training. Learning was represented by the change in participants’ scores from pre- to post-training. That is, learning scores were the difference between participants’ scores on the first and second administrations such that a positive learning score indicated improved knowledge after training. The average learning score was 4.18.

Time. Time was captured automatically by Qualtrics in two ways. First, time spent in the study was measured using participants’ start and finish timestamps. That is, time in study was measured as the entire time participants spent in the study from the moment they viewed the consent through the time they submitted their final responses and saw the debrief information. Second, time on task was measured using Qualtrics’ page timing feature, which measures the

length of time participants spend on each page of the study. Calculating the total time participants committed to training (e.g., reading training materials, watching videos) versus non-training (e.g., reading the consent, completing demographic measures) activities provides a precise measurement of time on task.

Self-regulatory activity. Self-regulation activity was measured with an 18-item scale developed by Sitzmann and Ely (2010; see Appendix E for the full scale). Theory suggests that self-regulatory processes are reciprocal (Bandura, 1986; Pintrich, 2000; Vancouver & Day, 2005), and strongly related to one another. Thus, three self-reported self-regulation constructs – concentration, metacognition, and motivation – were measured and combined to provide an overall indicator of participants’ self-regulatory activity during training. Concentration was assessed with six items adapted from Lee, Sheldon, and Turban (2003; e.g., “During the training, I had good concentration”). Metacognition was assessed with six items adapted from Ford et al. (1998; e.g., “While learning Excel, I monitored how well I was learning the material”). Motivation was assessed with six items adapted from Noe and Schmitt (1986; e.g., “I tried to learn as much as I could from this Excel module”). Responses were on a 5-point Likert scale ranging from 1 = *strongly disagree* to 5 = *strongly agree*. Correlations between the sub-scales (i.e., concentration, motivation, and metacognition) ranged from -0.20 to 0.23. Reliability of the combined scale was 0.63. Reliabilities for the concentration, metacognition, and motivation subscales were 0.59, 0.67, and 0.91, respectively.

Cognitive ability. Cognitive ability was measured using participants’ self-reported SAT and ACT scores. Research has demonstrated that SAT and ACT tests largely measure general mental ability (Frey & Detterman, 2004). Furthermore, extant findings show that self-reported

SAT and ACT scores highly correlate with actual performance scores. Gully, Payne, Koles, and Whiteman (2002) found that self-reported and actual scores correlated 0.95, and Cassady (2001) showed them to be correlated 0.88. ACT scores were converted to a compatible SAT score using the comparison tables presented in Appendix F (ACT, 2008). Resulting SAT component scores (i.e., SAT critical reading, mathematics, and writing scores) were totaled and used as a proxy measure for cognitive ability. Pre-2005 SAT scores were converted from the 1600 scale to a comparable score on the current 2400 point scale using the comparison chart in Appendix G.

Manipulation check. Five questions were written specifically for the current study in order to determine participants' sensitivity to the experimental conditions (Appendix H). An example item is, "During training, I received questions that asked me about my learning process." Participants answered the questions with a 'Yes' or 'No'.

Internal Review Board Submission Decision

Prior to data collection, the study protocol was submitted to the University of Central Florida's (UCF) Internal Review Board (IRB). The study was approved on June 10, 2014 (see Appendix I for approval letter) and data collection began on June 11, 2014.

Data Analysis

Analyses for this study were conducted using IBM SPSS Statistics version 21.0 for Windows. Due to the conditional process (i.e., stage 1 moderated mediation; Edwards & Lambert, 2007) nature (Hayes, 2007) of the proposed model, hypotheses were tested with path analytic procedures (Edwards & Lambert, 2007; Preacher, Rucker, & Hayes, 2007), which have been shown to have the best performance for testing moderated mediation models (MacKinnon, Lockwood, Hoffman, West, & Sheets, 2002). Specifically, hypotheses were tested with ordinary least squares (OLS) regression using Hayes' (2013) PROCESS macro (Model 7) to estimate the hypothesized model and obtain bias-corrected bootstrapped confidence intervals (using 5,000 bootstrap samples) for the conditional indirect effects. Hayes' macro allows for simultaneous testing of entire models that combine mediation and moderation to explore the conditional nature of indirect effects, as is now recommended by methodologists (Edwards & Lambert, 2007; Preacher et al., 2007).

CHAPTER FOUR: RESULTS

Data Filtering

A total of 303 cases were collected for the current study. Of these, 55 participants dropped out before completing the study and were excluded from analysis, leaving 248 participants. In the second stage of participant filtering, another 11 participants were removed from the sample for participating in the study twice. Only their second attempt was excluded from the sample, leaving 237 cases. Because learners were able to control the content they saw, it was possible for participants in the experimental condition to skip content that included the self-regulation prompts and complete training without seeing any or all prompts. The third step of data filtering was to remove the 16 cases assigned to the experimental condition for responding to fewer than all 12 of the self-regulation prompts. The sample size was reduced to 221 as a result. Finally, although time in study did not prove to be a good indicator of time spent reviewing training materials (discussed in detail below), it was possible to use this variable to remove participants who spent so little time in the study that it was unlikely they were engaged enough in the study to have provided reliable data. A floor cutoff value of 25 minutes was used to eliminate potential random responders and individuals who were unlikely to have taken time to consider the training content of interest to them. All study measures could be completed in approximately 20 minutes. Since the training provided learner control over the content they decided to view, five minutes is the approximated minimum amount of time needed for participants to review the content available to them, decide what content, if any, was relevant to

extending their knowledge of Microsoft Excel, and review content of one topic area. An additional 62 participants were removed for spending less than 25 minutes in the study. Table 5 reports the sample sizes across study variables and conditions. Due to missing data, the sample size is smaller for the cognitive ability variable as compared to the other variables, which were calculated from complete data. However, as discussed below, cognitive ability was not used as a covariate in the final analyses, allowing for a final sample of 159 participants, 81 of which were in the control group and 78 in the treatment (i.e., experimental) group.

During data cleaning, I noticed discrepancies in the page timing data captured by Qualtrics. Complete page timing data were available for only 50.3% of the sample and estimates of time in study generated from these data did not significantly correlate with time in study as measured by the start and end timestamps ($r = 0.06, p = 0.43$). I expected the correlation to be much higher, given they were different measures of the same variable (i.e., time in study). I took this finding to indicate that even when complete page timing data were available, they did not accurately reflect actual time spent on each page of the study. Qualtrics support was contacted by phone and confirmed that they were aware of a malfunction in the timing feature and that their software programmers were currently working to identify and fix the issue(s). Unfortunately, there was no way to retrieve or update the page timing data as it had not been accurately recorded while participants' were in the study.

Since time on task was not measured as planned and could not be used as a reliable index of time spent reviewing training materials, I conducted an exploratory post hoc independent samples t-test to assess whether the time in study data as measured using start and end times could replace the page timing metric as a proxy measure of time on task. Given that time in study

demonstrated significant positive skewness of 6.24 ($SE = 0.19$), I conducted a log transformation, which reduced the distribution's skewness to 1.95 ($SE = 0.19$). The results of an independent samples t-test comparing both study conditions (experimental versus control) on the log transformed time in study variable was statistically non-significant [$t(157) = -0.24, p = 0.81$]. Furthermore, the minimum value for time in study (prior to excluding anyone who spent less than 25 minutes in the study) was 5.35 minutes whereas the maximum value was 14,956.00 minutes (i.e., 10.37 days). Clearly, some participants did not take the study seriously and sped through the measures and training at an unrealistic rate while other participants left the study open for such extended periods of time it is not possible that they were engaged in the tasks for the entire duration. These results indicated that time in study as measured with start and finish timestamps was not an appropriate proxy estimate of time spent reviewing the training materials since I could not infer how much time individuals who had the study open for days on end were actually committing to the training. Therefore, the hypotheses concerning time on task (Hypotheses 1a, 3a, and 4a) could not be tested in this study.

Correlational Results

Table 5 reports the sample sizes, means, standard deviations, reliabilities (Cronbach's alpha), and zero-order Pearson product-moment correlations among study variables for the overall sample, control group, and treatment group. Cognitive ability was not statistically significantly related to any of the study variables. As such, it was excluded from further analysis

following recommendations (e.g., Becker, 2005; Carlson & Wu, 2012). Prove performance goal orientation was not significantly related to self-regulatory activity ($r = 0.07, p = 0.40$) nor learning ($r = 0.08, p = 0.41$). Self-regulatory activity was not significantly related to learning ($r = -0.01, p = 0.89$).

Table 5. Sample Size, Means, Standard Deviations, Reliabilities, and Zero-Order Correlations between Study Variables

	<i>N</i>	<i>M</i>	<i>SD</i>	1	2	3	4
1. Cognitive ability							
Overall	116	1689.16	221.58	--			
Control	57	1687.98	205.03	--			
Treatment	59	1690.29	238.24	--			
2. Prove performance goal orientation							
Overall	159	4.42	0.89	0.00	(0.73)		
Control	81	4.47	0.87	0.08	(0.72)		
Treatment	78	4.36	0.92	-0.06	(0.74)		
3. Self-regulatory activity							
Overall	159	2.91	0.32	-0.05	0.07	(0.63)	
Control	81	2.90	0.31	0.01	0.07	(0.62)	
Treatment	78	2.93	0.34	-0.11	0.07	(0.64)	
4. Learning							
Overall	159	4.18	3.76	-0.08	-0.07	0.08	--
Control	81	3.84	3.73	-0.07	-0.19	-0.02	--
Treatment	78	4.53	3.79	-0.09	0.06	0.16	--

Note. Cronbach's alphas are reported on the diagonal. *N* = sample size for overall, control group, and treatment group for each respective study variable. Due to missing data, cognitive ability suffered from a smaller sample size but was not included in analyses given its non-significant correlations with the study variables. The final sample used in the current study was 159.

** $p < 0.01$, * $p < 0.05$, † $p < 0.10$

Reliability

As shown in Table 5, the reliability of prove performance goal orientation ($\alpha = 0.73$) was above the accepted standard of 0.70 (Nunnally & Bernstein, 1994). However, self-regulatory activity ($\alpha = 0.63$) did not meet the accepted threshold for reliability. Examination of the subscales showed that the concentration ($\alpha = 0.59$) and metacognition ($\alpha = 0.67$) subscales were under-performing (see Table 6). Further investigation showed that a minimally desired Cronbach's alpha value of 0.70 could be obtained by removing four of the six concentration items and one of the six metacognition items. However, deleting 5 items unevenly across the subscales would compromise the scale's integrity and was a drawback not outweighed by the benefit of an alpha value improved by 0.07. Therefore, all analyses are conducted using the full scale.

Table 6. Means, Standard Deviations, Reliabilities, and Zero-Order Correlations between Self-Regulatory Activity Subscales

Scale	1	2	3
1. Concentration Subscale	(0.59)		
2. Motivation Subscale	-0.20*	(0.91)	
3. Metacognition Subscale	0.23**	-0.20*	(0.67)

Note. Cronbach's alphas (α) are reported on the diagonal.

* $p < 0.05$, ** $p < 0.01$

Between Group Comparisons

Before testing the hypotheses, a series of one-way between-groups analysis of variance (ANOVA) was conducted to explore the impact of sample source on cognitive ability, prior knowledge, prove performance goal orientation, self-regulation activity, and learning. Participants were divided based on their source (Group 1: UCF, Group 2: Quinnipiac University [QU], Group 3: Clemson University [CU], Group 4: University of South Florida [USF], Group 5: Social Media). Results of these analyses are reported in Table 7. There was not a statistically significant difference at the $p < 0.05$ level in cognitive ability [$F(4, 111) = 1.78, p = 0.14$], prior knowledge [$F(4, 154) = 2.34, p = 0.06$], prove performance goal orientation [$F(4, 154) = 1.02, p = 0.40$], self-regulation activity [$F(4, 154) = 0.38, p = 0.83$], nor learning [$F(4, 154) = 0.90, p = 0.47$] scores for the five data sources. The lack of statistically significant differences between the sample sources on these groups indicate that they are statistically equivalent, and can be combined in further analyses. Sample sizes, means, and standard deviations for each of the data source groups on the study variables are reported in Table 8.

A series of independent-samples t-tests was conducted to compare the cognitive ability, prove performance goal orientation, and prior knowledge scores of the control and treatment (i.e., experimental) conditions. Results of the independent-samples t-tests are presented in Table 9. There was no significant difference in cognitive ability [$t(114) = -0.06, p = 0.96$], prior knowledge [$t(157) = 1.32, p = 0.19$], nor prove performance goal orientation [$t(157) = 0.44, p = 0.44$] scores between the two conditions. These results suggest that the two conditions were statistically equivalent on the study variables before participation in training.

Table 7. Results of One-Way Analysis of Variance (ANOVA) between Data Sources and Study Variables

	<i>n</i>	<i>df</i>	<i>F</i>	<i>p</i>
Cognitive ability	116	4	1.78	0.14
Prior knowledge	159	4	2.34	0.06
Prove performance goal orientation	159	4	1.02	0.40
Self-regulation activity	159	4	0.38	0.83
Learning	159	4	0.90	0.47

Table 8. Data Source Descriptive Statistics for Study Variables

	<i>n</i>	<i>M</i>	<i>SD</i>	Minimum	Maximum
Cognitive ability					
1: UCF	96	1683.88	203.86	1120.00	2260.00
2: QU	7	1617.14	251.11	1350.00	2050.00
3: CU	8	1667.50	368.70	820.00	1950.00
4: USF	1	1810.00	--	--	--
5: Social Media	4	1955.00	96.78	1840.00	2040.00
Prior knowledge					
1: UCF	127	7.69	2.84	2.00	15.00
2: QU	10	8.40	3.69	2.00	14.00
3: CU	13	6.92	2.50	2.00	12.00
4: USF	4	11.50	3.87	7.00	16.00
5: Social Media	5	7.86	2.98	7.00	11.00
Prove performance goal orientation					
1: UCF	127	4.39	0.94	1.00	6.00
2: QU	10	4.75	0.62	4.00	6.00
3: CU	13	4.38	0.52	4.00	6.00
4: USF	4	5.00	0.54	4.00	6.00
5: Social media	5	4.05	0.82	3.00	5.00
Self-regulation activity					
1: UCF	127	2.92	0.32	1.72	3.72
2: QU	10	2.97	0.26	2.61	3.33
3: CU	13	2.83	0.43	1.67	3.44
4: USF	4	2.85	0.16	2.61	2.94
5: Social media	5	2.96	0.42	2.39	3.33
Learning					
1: UCF	127	4.02	3.95	-4.00	13.00
2: QU	10	4.00	3.06	-1.00	8.00
3: CU	13	5.46	2.79	1.00	11.00
4: USF	4	3.00	1.83	1.00	5.00
5: Social media	5	6.200	2.86	2.00	10.00

Table 9. Results of Independent Samples T-tests between Study Conditions

	<i>n</i>	<i>df</i>	<i>t</i>	<i>p</i>	<i>95% Confidence Interval</i>	
					<i>Lower</i>	<i>Upper</i>
Cognitive ability	116	114	-0.06	0.96	-84.18	79.57
Prior knowledge	159	157	1.32	0.19	-0.30	1.52
Prove performance goal orientation	159	157	0.78	0.44	-0.17	0.39

Manipulation Check

I tested the objective functionality of Qualtrics by determining that participants in the experimental condition received the self-regulation prompts and not the technology readiness items while the control condition received technology readiness items and not the self-regulation prompts. To do so, I totaled the number of self-regulation prompts and technology readiness items each participant received and cross-referenced them with the study conditions. As expected, participants in the control group received only the technology readiness items whereas the participants in the experimental group received only the 12 self-regulation prompts.

In order to assess how study participants perceived the manipulation, I examined the control and experimental groups' response patterns to the five manipulation check items. I anticipated that participants in the experimental group would respond with 'yes' to the three items asking about the presentation of prompts during training (Items 1-3) and 'no' to the two items regarding technology (Items 4 and 5). The opposite pattern was expected of the control group. As can be seen in Table 10, the pattern of responses was not quite as clear as expected. Three items (i.e., Item 3, "During training, I received questions that asked me about my learning

progress”, Item 4, “After training, I was asked my opinions about technology”, and Item 5, “After training, I received questions about technology) demonstrated the expected response pattern across both groups.

Table 10. Group Responses to Manipulation Check Items

Item	Control Group		Experimental Group	
	Yes	No	Yes	No
1. During training, I was periodically prompted to ask myself questions about my learning.	59.3%	40.7%	74.4%	25.6%
2. During training, I had to ask myself questions about the learning strategies I was using.	63.0%	37.0%	62.8%	37.2%
3. During training, I received questions that asked me about my learning progress.	43.2%	56.8%	84.8%	15.2%
4. After training, I was asked my opinions about technology.	91.4%	8.6%	32.1%	67.9%
5. After training, I received questions about technology.	92.6%	7.4%	48.7%	51.3%

Note. Percentages in bold indicate where the actual pattern of results of the group matches its expected pattern.

Tests of Hypotheses

As discussed above, Hypotheses 1a, 3a, and 4a could not be tested because the measure of time participants spent reviewing training materials did not work correctly and an adequate proxy measure was not available. Therefore, the following sections only present the results for Hypotheses 1b, 2, 3b, and 4b.

Direct effect of prompts. Hypothesis 1b stated that learners who are prompted to self-regulate will engage in more self-regulatory activity than learners who are not prompted to self-

regulate. Similarly, Hypothesis 2 suggested that learners who are prompted to self-regulate will learn more from training than participants who do not receive self-regulation prompts. The direct effects of self-regulation prompts on self-regulatory activity and learning were examined. As can be seen in Table 11, prompts did not have a statistically significant effect for self-regulatory activity [$B = 0.03$, $t(155) = 0.13$, $p = 0.90$] nor learning [$B = 0.66$, $t(155) = 1.10$, $p = 0.27$]. Thus, Hypotheses 1b and 2 were not supported.

Indirect effect of prompts. Hypothesis 3b stated that the effect of self-regulation prompts will be mediated by self-regulatory activity. This hypothesis was tested by examining the indirect effect of prompts on learning via its influence on self-regulatory activity. Table 12 presents the conditional indirect effects of these self-regulation processes using the normal theory approach and 95% bias-corrected bootstrap confidence intervals. Hayes (2013) recommends the use of bootstrap confidence intervals for determining significance of conditional indirect effect. In Table 12, the conditional indirect effect [$\omega = (a_1 + a_3W)b_1$] for self-regulatory activity is shown at three values of prove performance goal orientation: one standard deviation below the mean ($-1SD = 3.53$), the mean ($M = 4.42$), and one standard deviation above the mean ($1SD = 5.31$). Interpretation of both the p -values (normal theory approach) and confidence intervals (bootstrap approach) suggests that, contrary to Hypotheses 3b, there was not a conditional indirect effect for self-regulatory activity, regardless of the level of prove performance goal orientation. All confidence intervals included zero and $p > 0.05$. Thus, Hypothesis 3b was not supported.

Conditional effect of prove performance goal orientation. Hypothesis 4b suggested that prove performance goal orientation moderates the relationship between self-regulation

prompts and self-regulatory processes such that self-regulation prompts will be more positively related to self-regulatory activity when learners are more highly prove performance goal oriented. As shown in Table 11, there was no effect for the interaction between self-regulation prompts and prove performance goal orientation on self-regulatory activity [$B = 0.00$, $t(155) = 0.01$, $p = 1.00$]. Thus, Hypothesis 4b was not supported.

Table 11. Predictors of Time on Task, Self-regulatory Activity, and Learning

Predictor	Consequent: Self-regulatory Activity					
	<i>B</i>	<i>SE</i>	<i>t</i>	<i>p</i>	95% Confidence Interval	
					<i>Lower Bound</i>	<i>Upper Bound</i>
Constant	2.79	0.19	14.64	0.00	2.41	3.16
Prompts	0.03	0.26	0.13	0.90	-0.48	0.55
PPGO	0.03	0.04	0.61	0.55	-0.06	0.11
Prompts × PPGO	0.00	0.06	0.01	1.00	-0.11	0.12
$R^2 = 0.01$						
$F(3, 155) = 1.05, p = 0.35$						
Predictor	Consequent: Learning					
	<i>B</i>	<i>SE</i>	<i>t</i>	<i>p</i>	95% Confidence Interval	
					<i>Lower Bound</i>	<i>Upper Bound</i>
Constant	1.47	2.73	0.54	0.59	-3.92	6.86
Prompts	0.66	0.60	1.10	0.27	-0.52	1.84
Self-regulatory Activity	0.82	0.93	0.88	0.38	-1.02	2.65
$R^2 = 0.01$						
$F(2, 156) = 1.05, p = 0.35$						
<i>Note.</i> PPGO = Prove Performance Goal Orientation						

Table 12. Conditional Indirect Effects of Prompts in Relation to Learning

Conditional Effects of Self-regulatory Activity at PPGO = Mean +/- 1SD						
PPGO	$\omega = (a_1 + a_3W)b_1$	SE_ω	z	p	95% Bias-Corrected Bootstrap Confidence Interval	
					Lower Bound	Upper Bound
3.53	0.03	0.09	0.34	0.73	-0.06	0.36
4.42	0.03	0.06	0.44	0.66	-0.04	0.28
5.31	0.03	0.10	0.31	0.76	-0.08	0.37

Note. PPGO = Prove Performance Goal Orientation. $N = 159$. The conditional indirect effect is calculated by $(a_1 + a_3W)b_1$, where a_1 is the path from prompt to learning, a_3 is the path from the interaction of prompts and the mediator (self-regulatory activity), W is PPGO, and b_1 is the path from the mediator (self-regulatory activity) to learning.

Exploratory Analysis

In addition to analysis of the hypothesized relationships, I conducted exploratory analyses with the intention of better understanding the results of the current study. Specifically, I wanted to explore the possible threats of Type II error that might be present in my study which would inhibit my ability to detect relationships among the study variables.

Obligation to self-regulate. One reason why I may have failed to find direct effects of self-regulation prompts on time on task, self-regulatory activity, and learning, is that participants may already have been high in their perception of needing to self-regulate during training. As demonstrated in Table 11 above, participants in both conditions tended to agree with statements that they were encouraged to think about their learning (i.e., self-regulate) during training.

Indeed, further analysis using a chi-square test for independence indicates that there is not a significant difference between the response patterns of the control and experimental groups for either Item 1 (“During training, I was periodically prompted to ask myself questions about my

learning”) [$\chi^2(1, N = 156) = 3.43, p = 0.06$] or Item 2 (“During training, I had to ask myself questions about the learning strategies I was using”) [$\chi^2(1, N = 156) = 0.00, p = 1.00$]. There was, however, a significant difference between how the experimental and control groups responded to Item 3 (“During training, I received questions that asked me about my learning progress”) [$\chi^2(1, N = 156) = 27.64, p = 0.00$]. Table 13 presents the results of the chi-square test for independence.

Table 13. Results of the Chi-Square for Independence Tests between Group Responses to Manipulation Check Items

Items & Responses	Control N = 81		Experimental N = 78		χ^2	p
	n	%	n	%		
1. During training, I was periodically prompted to ask myself questions about my learning.						
Yes	48	59.30	58	74.40	3.43	0.06
No	33	40.70	20	25.60		
2. During training, I had to ask myself questions about the learning strategies I was using.						
Yes	51	63.00	49	62.80	0.00	1.00
No	30	37.0	29	37.20		
3. During training, I received questions that asked me about my learning progress.						
Yes	35	43.20	66	84.60	27.64	0.00
No	46	56.80	12	15.40		
4. After training, I was asked my opinions about technology.						
Yes	74	91.40	25	32.10	56.99	0.00
No	7	8.60	53	67.90		
5. After training, I received questions about technology.						
Yes	75	92.60	38	48.70	35.10	0.00
No	6	7.40	40	51.30		

Note. Yates’ Correction of Continuity and corresponding significance value is reported to correct for the overestimation of the Pearson chi-square value in 2×2 tests.

Manipulation saliency. A second explanation for why direct effects of self-regulation prompts were not observed in the current study is that the manipulation was not salient to participants. Results of the chi-square tests indicate that Manipulation Check Item 3 was most reflective of condition membership. As such, it is possible that those participants who responded as expected to this item were most sensitive to the manipulation. Anticipating that this subset of participants should behave as hypothesized, I reexamined the study hypotheses using only the participants in the experimental and control conditions who, respectively, answered ‘Yes’ and ‘No’ to Item 3.

As before, I tested the hypotheses with ordinary least squares (OLS) regression using Hayes’ (2013) PROCESS macro (Model 7) to estimate the model and obtain bias-corrected bootstrapped confidence intervals (using 5,000 bootstrap samples) for the conditional indirect effect. Results of the analysis on the restricted sample are reported in Table 14. Results were similar to the analyses conducted on the full sample. Even within the restricted sample there was no significant effect of self-regulation prompts for self-regulatory activity [$B = -0.02$, $t(108) = -0.08$, $p = 0.94$] nor learning [$B = 0.86$, $t(109) = 1.17$, $p = 0.24$]. Neither was there a significant effect for the interaction between prompts and prove performance goal orientation on self-regulatory activity [$B = 0.02$, $t(108) = 0.33$, $p = 0.74$]. However, the sample sizes of the control ($n = 46$) and experimental ($n = 66$) were unequal, so there is a higher risk of Type II error (accepting the null hypothesis when it is correct) when interpreting the results of this analysis.

Table 14. Predictors of Time on Task, Self-regulatory Activity, and Learning within the Restricted Sample

Predictor	Consequent: Self-regulatory Activity					
	<i>B</i>	<i>SE</i>	<i>t</i>	<i>p</i>	95% Confidence Interval	
					<i>Lower Bound</i>	<i>Upper Bound</i>
Constant	2.89	0.21	13.73	0.00	2.47	3.30
Prompts	-0.02	0.29	-0.08	0.94	-0.60	0.56
PPGO	0.00	0.05	0.05	0.96	-0.09	0.09
Prompts × PPGO	0.02	0.07	0.33	0.74	-0.11	0.15
$R^2 = 0.02$						
$F(3, 108) = 0.56, p = 0.64$						
Predictor	Consequent: Learning					
	<i>B</i>	<i>SE</i>	<i>t</i>	<i>p</i>	95% Confidence Interval	
					<i>Lower Bound</i>	<i>Upper Bound</i>
Constant	3.27	3.39	0.97	0.34	-3.44	9.99
Prompts	0.86	0.73	1.17	0.24	-0.59	2.31
Self-regulatory Activity	0.24	1.15	0.20	0.84	-2.05	2.52
$R^2 = 0.01$						
$F(2, 109) = 0.75, p = .48$						

Note. PPGO = Prove Performance Goal Orientation

Issues of reliability. Low reliability of the self-regulation activity measure could have obfuscated the relationship between self-regulation activity and other study variables. The motivation subscale demonstrated an acceptable level of reliability, though the metacognition and concentration scales did not (Table 6). In order to examine whether the null results demonstrated by the full self-regulatory activity scale could be driven by the low reliability, I examined the model again with metacognition, concentration, and motivation as separate mediators. I expected that if low reliability was the driver behind self-regulation activity's null relationships to the other study variables then motivation would become significant in the exploratory model whereas concentration and metacognition would remain non-significant. Results are presented in Table 15. Prompts did not significantly predict scores of concentration

[$B = -0.23$, $t(155) = -0.64$, $p = 0.52$], metacognition [$B = 0.32$, $t(155) = 0.81$, $p = 0.42$], nor motivation [$B = 0.02$, $t(155) = 0.02$, $p = 0.98$]. Furthermore, neither metacognition [$B = 0.16$, $t(155) = 0.25$, $p = 0.80$] nor concentration [$B = -0.98$, $t(155) = -1.43$, $p = 0.15$] were significantly related to learning. However, motivation was significantly related to learning [$B = 0.75$, $t(154) = 2.05$, $p = 0.04$].

Table 15. Predictors of Concentration, Metacognition, Motivation, and Learning

Consequent: Concentration						
Predictor	<i>B</i>	<i>SE</i>	<i>t</i>	<i>p</i>	95% Confidence Interval	
					Lower Bound	Upper Bound
Constant	3.48	0.27	13.09	0.00	2.96	4.01
Prompts	-0.23	0.37	-0.64	0.52	-0.96	0.49
PPGO	0.00	0.06	-0.01	0.99	-0.11	0.11
Prompts × PPGO	0.04	0.08	0.46	0.65	-0.12	0.20
$R^2 = 0.01$						
$F(3, 155) = 0.47, p = 0.71$						
Consequent: Metacognition						
Predictor	<i>B</i>	<i>SE</i>	<i>t</i>	<i>p</i>	95% Confidence Interval	
					Lower Bound	Upper Bound
Constant	1.95	0.29	6.72	0.00	1.38	2.53
Prompts	0.32	0.40	0.81	0.42	-0.47	1.11
PPGO	-0.06	0.06	-0.99	0.32	-0.19	0.06
Prompts × PPGO	-0.03	0.09	-0.38	0.71	-0.21	0.14
$R^2 = 0.05$						
$F(3, 155) = 2.98, p = 0.03$						
Consequent: Motivation						
Predictor	<i>B</i>	<i>SE</i>	<i>t</i>	<i>p</i>	95% Confidence Interval	
					Lower Bound	Upper Bound
Constant	2.92	0.47	6.01	0.00	1.96	3.88
Prompts	0.02	0.67	0.02	0.98	-1.30	1.33
PPGO	0.14	0.11	1.31	0.19	-0.07	0.35
Prompts × PPGO	0.00	0.15	-0.02	0.98	-0.30	0.29
$R^2 = 0.02$						
$F(3, 155) = 1.16, p = 0.33$						
Consequent: Learning						
Predictor	<i>B</i>	<i>SE</i>	<i>t</i>	<i>p</i>	95% Confidence Interval	
					Lower Bound	Upper Bound
Constant	4.33	2.99	1.44	0.15	-1.59	10.24
Prompts	0.60	0.60	0.99	0.32	-0.59	1.79
Concentration	-0.98	0.68	-1.43	0.15	-2.33	0.37
Metacognition	0.16	0.62	0.25	0.80	-1.07	1.39
Motivation	0.75	0.37	2.05	0.04	0.03	1.48
$R^2 = 0.06$						
$F(4, 154) = 2.25, p = 0.07$						

Note. PPGO = Prove Performance Goal Orientation

CHAPTER FIVE: DISCUSSION

The purpose of the current study was to investigate the influence prove performance goal orientation can have on the effectiveness of self-regulation prompts within a learner controlled e-learning environment. The current study contributes to the extant literature base by responding to Gully and Chen's (2010) call for research examining the effects of interactions between individual differences and training methodologies on the learning process. The current study explores this issue within the context of a relatively new training intervention that uses self-regulation prompts to overcome drawbacks inherent to learner controlled training. Although some research has investigated the relationships between self-regulatory prompts and training outcomes, such as learning (e.g., Berthold et al., 2007; Hübner et al., 2006; Nückles et al., 2009; Santhanam, Sasidharan, & Webster, 2008), and the processes through which prompts can operate (Sitzmann & Ely, 2010), this literature base is still nascent. The dissertation described here attempted to replicate previous findings supporting the utility of self-regulation prompts in learner controlled e-learning while also beginning to expand self-regulation prompting research into explorations of the conditional effects of individual difference variables (prove performance goal orientation).

It was hypothesized that individuals receiving self-regulation prompts during learner controlled training would spend more time reviewing the training materials, engage in greater amounts of self-regulation activity, and learn more than individuals who were not prompted to self-regulate during the same e-learning experience. Furthermore, it was predicted that the effect of self-regulation prompting on learning would be transmitted through its influence on self-

regulation processes. Finally, self-regulation prompts were hypothesized to interact with prove performance goal orientation to influence self-regulation processes. Specifically, the relationships between self-regulation prompts and time spent reviewing training materials and general self-regulatory activity were predicted to be more positive when learners are higher on prove performance goal orientation.

Contrary to previous similar work (e.g., Sitzmann & Ely, 2010), none of the study hypotheses were supported. I was unable to provide evidence that self-regulation prompts have the anticipated positive impact on self-regulation processes or learning. Furthermore, based on this study's findings, it does not appear that prove performance goal orientation has any impact on how well participants in learner controlled e-learning respond to self-regulation prompting. There were a number of possible reasons as to why study hypotheses were not supported. I discuss my findings from exploratory analyses of some of these possible explanations below.

Post Hoc Investigation

Methodological factors. From a methodological standpoint, it is possible that study findings were null due to problems with the measurement of the mediators, which are central to each hypothesis. As described above, there were technical issues that prevented precise measurement of the amount of time participants spent reviewing the training materials. The correlation between two different measures of time spent in the study was not significant, indicating that the more precise time measure (designed to capture only the time participants

spent reviewing training materials) was not reliable. Exploratory analysis indicated that an alternative measure of time participants spent in the study overall was not a reasonable proxy metric for time spent reviewing training materials. As such, the analyses pertaining to time on task could not be assessed in the current study.

Methodological issues with the self-regulatory activity scale rest on its sub-optimal reliability. Attempts to improve its consistency by removing underperforming items required removal of more than a quarter of the items unequally from each subscale in order to reach the minimally desired Cronbach's alpha. I believed this would compromise the integrity of the scale too greatly, so I did not feel justified in removing any items. Since analyses were conducted using the full scale, care must be taken when interpreting the results. Low reliability increases the risk that the study results underestimate the true relationship between self-regulation activity and the other study variables. It is entirely possible that I was unable to detect the relationships I hypothesized though they exist in reality. However, exploratory analyses of the subscales further demonstrated null relationships between study variables despite the increased risk of familywise (Type I) error introduced by analyzing these variables separately. The one exception was a direct relationship that emerged between motivation and learning. Though consistent with the literature, it may be that this relationship was a product of familywise error. Given that the motivation subscale demonstrated an acceptable level of reliability and was found to be directly related to learning, the results of these analyses lend credence to the conclusion that failure to detect an effect of prompts on self-regulation activity goes beyond issues of reliability. It may very well be that no effect was detected because these relationships do not exist in nature. However, not fully convinced of this, I further investigated alternative explanations.

Uniform feelings of obligation to self-regulate. Analysis of groups' responses to the manipulation check items indicated that there was not a significant difference between the experimental and control groups with regards to their feelings that they should have been self-regulating during training. The groups demonstrated statistically non-significant response patterns to the first two manipulation check items involving participants' perceptions of prompts. These two items ("During training, I was periodically prompted to ask myself questions about my learning" and "During training, I had to ask myself questions about the learning strategies I was using") were written to elicit 'yes' and 'no' responses from the experimental and control groups, respectively. Though the response pattern was contrary to expectations, it is possible that instead of measuring participants' perceptions of their exposure to prompts, these items actually capture the obligation to self-regulate participants experienced, irrespective of prompt exposure. For instance, perhaps most participants in a primarily college undergraduate sample inherently feel obligated to ask themselves questions about their learning strategies (item 2) as they progress through training, possibly as an artifact of the relatively high levels of learning goal orientation demonstrated in this sample ($M = 4.71$).

Supporting this argument is the difference in responses between the two groups to manipulation check item 3 ("During training, I received questions that asked me about my learning progress"). Item 3 more explicitly probed participants about the presence or absence of actual questions presented to them during training than did items 1 or 2. Responses indicate that when asked explicitly about whether they received questions (i.e., prompts), participants in the experimental condition were able to affirm their exposure. Control participants still appeared confused about what was being asked, but most (56.8%) were able to confirm that they did not

receive prompts. It is possible that the remaining 43.28% feared they had missed something important or that they should have received questions that they missed and so may have responded in the affirmative to protect their self-image. Indeed, these 44 individuals tended to be slightly more prove-performance goal oriented ($M = 4.57$) than both the average participant ($M = 4.42$) and those in the control group who responded 'no' ($M = 4.40$). Lying to appear competent is consistent with the profile of those high on prove performance goal orientation.

Manipulation saliency and strength. Exploratory analyses suggest that the study findings should not be related to a weak manipulation. When explicitly asked about prompts, most participants in the experimental condition (84.8%) indicated that they were aware of having received questions about their regulation. Clearly, most learners recognize exposure to prompts (saliency). However, analysis of a subsample expected to having been most affected by prompts still failed to support the study hypotheses.

Theoretical Implications

Gully and Chen (2010) underscored the important role of individual difference characteristics in training. They argued that individual differences are often underrepresented in training research and that more research is needed that consider the conditional influence they may have on the learning process and training outcomes. In light of the global trend towards technology-based learning (“e-learning”) that affords greater freedoms to learning, this study sought to contribute to research in this area. Prior research indicates that self-regulation prompts

may be a sensible solution for designing learner controlled e-learning environments that provide learners with their best chance at learning (Berthold et al., 2006; Sitzmann & Ely, 2010). Given the initial indication that self-regulation prompts are effective, this study answered Gully and Chen's call by investigating the conditional effect of self-regulation prompts for learners differing on levels of their prove performance goal orientation. However, the current study's results suggest that self-regulation prompts did not significantly affect learner performance and internal processing in the current learner controlled e-learning. Furthermore, this study indicates that this relationship was not conditionally related to learners' prove performance goal orientation profile.

Although the study results did not support self-regulation prompts as an effective training design element that encourages psychological learning processes and maximizes learning, they do have implications for how self-regulation activity and goal orientation may be studied. Internal self-regulation processes may not be best represented as a single mechanism and may instead be better understood using investigations that treated them separately. It is likely that these processes have differential relationships with training design features, such as self-regulation prompts, and individual difference characteristics (e.g., goal orientation). Combining them seems to only result in lost information that does not enable us to explore the nuances of how training design features operate. It seems probable that self-regulation prompts can be designed to target specific regulatory mechanisms (e.g., concentration) over others. Collapsing multiple mechanisms into a single construct prevents researchers from observing unique patterns of relationships between particular prompts and regulatory processes.

Finally, when contrasted with previous research, the results demonstrated in this study point towards motivations for participating in training more so than prove performance goal orientation as an important moderator of the relationships self-regulation prompts have with regulatory mechanisms and study outcomes. Sitzmann and Ely (2010), for example, investigated their hypotheses using a sample of volunteer participants who responded to an advertisement for Microsoft Excel training. While I attempted the same recruitment strategy as part of a battery of recruitment initiatives, I was much less successful with obtaining participants willing to participate in the study completely free of external incentives (e.g., extra credit). My sample came primarily from an undergraduate population (93.1%), most of who participated in order to earn class credit. These individuals may be willing to participate in the study in order to earn external rewards, but the lack of variance in their responses to the self-regulation activity scale suggests that they do not care whether they learn the materials. It may turn out that motivation to learn is the substantial difference in the positive findings found in the Sitzmann and Ely study compared to the null findings of this dissertation.

Practical Implications

The study described in this manuscript seems to indicate that collegiate learners may be less likely to benefit from self-regulation prompting when engaged in learner controlled e-learning. One possible explanation is that this demographic is too high on learning goal orientation for prompts to have much of an impact on their self-regulation. As generally highly

learning goal oriented, these individuals may already engage in as much regulation as they would barring the presence of much stronger motivators (e.g., verbal delivery of information, physical presence of another individual). Therefore, prompts may not be an effective design element to include in any learner controlled, technology-based training interventions. Neither do they appear to hinder performance, however. If resources allow, self-regulation prompts might be included in e-learning environments presented to university students, though they may not have much effect unless students are intrinsically motivated.

Limitations

There were several limitations worth mentioning that could have influenced the results and implications of this study. First, due to a technical malfunction, it was not possible to test the hypotheses predicting relationships between the time learners spend reviewing training materials and the other study variables. Second, the self-regulatory activity scale was unreliable in this sample. As discussed above, the low reliability may have contributed to the null findings. Although exploratory analyses provided some evidence that unacceptable reliability may not entirely explain the findings, it cannot be ignored as a limitation to the study. Third, the unreliability of the scale aside, there was no variance in how participants responded to the self-regulatory activity measures. This seems to indicate apathy towards the task. Though Microsoft Excel was chosen as the training content for the current study because it was believed that learning Excel would be a relevant skill of interest to many adults, it appears that collegiate

students only find such materials to be moderately engaging and do not have a strong internal desire to learn them. In short, it appears that the participants were in it for the research credit and that this culminated in moderate engagement with very little variance across individuals. They found the task mildly interesting but really cared primarily for the credits. It seems that the deception which was intended to activate participants' prove performance goal orientation may not have been strong enough to provide additional incentive to the students. Participants may not have believed that they would actually be required to submit their learning scores or, if they did, may not have cared since there were no consequences to doing poorly. Finally, there was no reliable way to screen out random responders from the dataset. I removed anyone who spent less than 25 minutes in the entire study as it is unlikely anyone could honestly and reasonably respond to the study measures and thoroughly assess the material content in less time. However, this approach to screening data does not guarantee that all random responders were removed. It is possible that some random responders remain in the dataset, confounding the study findings.

Future Directions

There are a number of future directions that I can recommend for research on self-regulation prompting in learner controlled e-learning environments. The content, amount, and delivery medium may all influence how well self-regulation prompts work. For instance, future research should explore whether the frequency and/or quantity of prompts makes a difference and whether there is a "sweet spot" or ideal ratio of prompts to content. There may be an inverse

relationship between prompts and self-regulation. Too few prompts may be easily ignored or overlooked whereas prompts that come too frequently may lose their novelty.

Future research should also begin to unpack the individual mechanisms through which self-regulation prompts operate and whether the message content contained in prompts differentially affects regulatory mechanisms. A recent meta-analysis identified six major regulatory mechanisms within the self-regulation domain (Sitzmann & Ely, 2011). These include effort (amount of time devoted to learning; Brown, 2001; Fisher & Ford, 1998, Sitzmann & Ely, 2011; Wilhite, 1990), metacognitive strategies (planning and monitoring goal-directed behavior and employing learning techniques that help learners elaborate and integrate concepts into memory (Ford et al., 1998; Schraw & Dennison, 1994; Sitzmann & Ely, 2011), attention (i.e., concentration and maintenance of mental focus on instructional material throughout training; Lee et al., 2003; Sitzmann & Ely, 2011; Weinstein, Schulte, & Palmer, 1987), motivation (learners' willingness to engage in learning and desire to learn the course content; Noe, 1986; Sitzmann & Ely, 2011), time management (i.e., scheduling and allocating time for study activities), and environmental structuring (i.e., choosing a study location conducive to learning; Sitzmann & Ely, 2011). While some of these processes (e.g., effort, attention, metacognition, and motivation) have been explored in this and other research initiatives, to my knowledge, others (e.g., environmental structuring, time management) have as yet been examined. Future research on unpacking regulatory processes should include these as part of their investigations.

Conclusion

We are living in an age of electronic-based technology that is heavily embedded in our day-to-day activities and computer-based instruction is now a familiar means for delivering training (Brown & Ford, 2002; DeRouin et al., 2004, 2005; Eschenmann, 2012; Hughes et al., 2013; Kosarzycki et al., 2003; Orvis et al., 2010). A feature of many e-learning programs is learner control, which offers trainees greater freedoms in dictating how, when, and where they learn. Unfortunately, learner control in training is not uniformly beneficial and in the worst circumstances may even be harmful to learning (e.g., Carolan et al., 2014; Kraiger & Jerden, 2007). However, it is unrealistic in modern society to recommend disuse of learner control, particularly when it is so easy to include as a feature of e-learning platforms. Therefore, the challenge becomes designing e-learning training programs that have the best chance of being effective.

Self-regulation prompts are one such training design feature that have shown promise for overcoming potential drawbacks associated with learner controlled e-learning (Sitzmann & Ely, 2010). In order to advance research related to this design feature, the purpose of this study was to respond to Gully and Chen's (2010) recommendation for more investigation of the interaction between training design elements and individual differences. I examined a moderated mediation model to explain how self-regulation prompts affect self-regulation processes and subsequent learning and for whom prompts are most effective. Findings did not support the hypotheses. No effect was found for self-regulation prompts as a design feature that can enhance learning via self-regulatory processing during training. Neither was I able to demonstrate that the

effectiveness of self-regulation prompts is a function of learners' prove performance goal orientation.

Although the lack of findings consistent with prior research and in support of the study hypotheses is interesting, they are by no means the final verdict, as substantial research is needed in this crucial area. It is very likely that there are other conditions that influence when and for whom prompts are helpful. It is my hope that this study will inspire future research and that others will continue to explore the role of self-regulation prompts in learner controlled e-learning.

APPENDIX A: SELF-REGULATION PROMPTS

Self-regulation Prompts

Self-regulation prompts developed by:

Sitzmann, T., & Ely, K. (2010). Sometimes you need a reminder: The effects of prompting self-regulation on regulatory processes, learning, and attrition. *Journal of Applied Psychology, 95*, 132-144.

SCALE:

[1 = Not At All, 2 = Minimally, 3 = Somewhat, 4 = Mostly, 5 = Definitely]

Self-Regulation Prompts

1. Am I setting goals to ensure I have a thorough understanding of the training material?
2. Do I know enough about the training material to remember the material after I finish the course?
3. Do I know enough about the training material to answer all the questions correct on the quiz for this module?
4. Am I concentrating on learning the training material?
5. Do I understand all of the key points of the training material?
6. Are the study strategies I'm using helping me learn the training material?
7. Have I spent enough time reviewing to remember the information after I finish the course?
8. Am I setting goals to help me remember the material after I finish the course?
9. Would I do better on the final exam if I studied more?
10. Am I focusing my mental effort on the training material?
11. Do I need to continue to review to ensure I will remember the material after I finish the course?
12. Are the study tactics I have been using effective for learning the training material?

APPENDIX B: TECHNOLOGY READINESS INDEX

Technology Readiness Index developed by Parasuraman, A. (2000). Technology readiness index: A multiple-item scale to measure readiness to embrace new technologies. *Journal of Service Research*, 2(4), 307-320.

SCALE

[1 = Strongly Disagree, 2 = Disagree, 3 = Somewhat Agree, Somewhat Disagree, 4 = Agree, 5 = Strongly Agree.]

Technology Readiness

1. Technology gives people more control over their daily lives.
2. Products and services that use the newest technologies are much more convenient to use.
3. I like the idea of doing business via computers because I am not limited to regular business hours.
4. I prefer to use the most advanced technology available.
5. I like computer programs that allow me to tailor things to fit my own needs.
6. Technology makes me more efficient in my occupation.
7. I find new technologies to be mentally stimulating.
8. Technology gives me more freedom of mobility.
9. Learning about technology can be as rewarding as the technology itself.
10. I feel confident that machines will follow through with what I instruct them to do.
11. I find I am doing more things now with advanced technology than a couple years ago.
12. I find that technology designed to make life easier usually has disappointing results.

Reverse scored

APPENDIX C: PROVE PERFORMANCE GOAL ORIENTATION SCALE

A Prove Performance Goal Orientation Scale developed by:
VandeWalle, D. (1997). Development and validation of a work domain goal orientation instrument. *Educational and Psychological Measurement*, 57(6), 995-1015.

SCALE:

[1 = Strongly Disagree, 2 = Disagree, 3 = Slightly Disagree, 4 = Slightly Agree, 5 = Agree, 6 = Strongly Agree]

Prove Performance Goal Orientation

1. I'm concerned with showing that I can perform better than my coworkers.
2. I try to figure out what it takes to prove my ability to others at work.
3. I enjoy it when others at work are aware of how well I am doing.
4. I prefer to work on projects where I can prove my ability to others.

APPENDIX D: MICROSOFT EXCEL 2013 KNOWLEDGE SCALE

Microsoft Excel 2013 Knowledge Scale adapted from:
GCF. (2014). Excel 2013. *GCFLearnFree*. Retrieved August 4, 2014, from
<http://www.gcflearnfree.org/excel2013>.

SCALE

Bold typeface denotes correct answer

Excel Basics

1. Which toolbar contains most of the commands that you will need in Excel?
 - a. **Ribbon**
 - b. Taskbar
 - c. Quick Access Toolbar
 - d. Menu bar
2. In order to share a workbook online, you must first _____.
 - a. **Save it to your OneDrive**
 - b. Save it as a PDF file
 - c. Open AutoRecover
 - d. Publish it as a webpage
3. To continue a series of dates, you can click and drag the _____.
 - a. AutoFill
 - b. AutoDate
 - c. **Fill handle**
 - d. Populate handle
4. How do you widen a column to fit your text?
 - a. Highlight the column and click Ctrl + W
 - b. Highlight the column and click Column Width in the user interface Ribbon
 - c. Double-click on the line to the left of a column
 - d. **Double-click on the line to the right of the column**
5. If you want to display a date in a certain way (such as Friday, March 1, 2013), you can adjust the _____.
 - a. Theme
 - b. Font
 - c. **Number format**
 - d. Cell value display
6. Grouping worksheets allows you to _____.
 - a. Give several worksheets the same name
 - b. Share a worksheet with a group of coworkers
 - c. Reference data across worksheets
 - d. **Make changes to multiple worksheets at once**

Formulas and Functions

7. When you create a formula, you'll always start by typing the _____ sign.
 - a. + (plus)
 - b. = (equal)**
 - c. / (slash)
 - d. ^ (caret)
8. Which operation will Microsoft Excel perform first in the following equation:
 $=D1/5+1*D3/(D3-D2)?$
 - a. D1/5
 - b. 5+1
 - c. 1*D3
 - d. D3-D2**
9. When making an absolute cell reference, you will need to include at least one _____.
 - a. % (percent sign)
 - b. ! (exclamation point)
 - c. \$ (dollar sign)**
 - d. & (ampersand)
10. Which function would you use to add the values of several cells?
 - a. SUM**
 - b. AVERAGE
 - c. ADD
 - d. TOTAL

Working with Data

11. Freezing panes allows you to _____.
 - a. Prevent others from editing your workbook
 - b. Protect row(s) or column(s) from changes
 - c. Lock row(s) or column(s) in place**
 - d. Hide row(s) or column(s)
12. If you want to rearrange rows by day of the week, you should use the _____ function.
 - a. Auto arrange
 - b. Filtering
 - c. Custom sort**
 - d. AutoFill
13. If you wanted to filter data to exclude a certain word or phrase, you could use a(n) _____.
 - a. Specialized text filter
 - b. Custom text filter
 - c. Super text filter
 - d. Advanced text filter**
14. The Subtotal command will automatically _____ your data.
 - a. Color code
 - b. Group, outline, and summarize**
 - c. Alphabetize

- d. Sort and filter
- 15. Whenever you format data as a table, it will automatically include _____.
 - a. Number formatting
 - b. Banded columns
 - c. Filters**
 - d. Frozen rows
- 16. When reading a chart, you should refer to the _____ to see which color is used to represent each data series.
 - a. Legend**
 - b. Title
 - c. Horizontal axis
 - d. Vertical axis
- 17. One advantage of sparklines is that _____.
 - a. They contain animated “sparks”
 - b. They are larger than normal charts
 - c. They have more types and features than normal charts
 - d. You can keep them very close to their source data**

Doing More with Excel

- 18. Which of the following is a way to edit the appearance of text based on cell values?
 - a. AutoFormat
 - b. Conditional Format**
 - c. Filter data
 - d. Copy and Paste
- 19. Slicers are basically just _____.
 - a. Sparklines
 - b. Tables
 - c. Filters**
 - d. Banded rows
- 20. Goal Seek allows you to _____.
 - a. Compare multiple scenarios at the same time
 - b. Work backward to find the desired input value**
 - c. Create a data table
 - d. Automatically round down

APPENDIX E: SELF-REGULATORY ACTIVITY SCALE

Self-Regulatory Activity Scale developed by:

Sitzmann, T., & Ely, K. (2010). Sometimes you need a reminder: The effects of prompting self-regulation on regulatory processes, learning, and attrition. *Journal of Applied Psychology, 95*(1), 132-144.

SCALE

[1 = Strongly Disagree, 2 = Disagree, 3 = Somewhat Agree, Somewhat Disagree, 4 = Agree, 5 = Strongly Agree]

Concentration

1. During the training, I had good concentration
2. During the training, I became easily absorbed in the training material
3. During the training, I found my mind wandering to other things. *Reverse coded.*
4. During the training, I felt distracted and found it hard to pay attention. *Reverse coded.*
5. During the training, I had to work hard to keep my mind on-task. *Reverse coded.*
6. During the training, I had a difficult time focusing on the training material. *Reverse coded.*

Metacognition

1. While learning Excel, I monitored how well I was learning the material.
2. I thought about whether I would remember the information already covered in training before moving on to the next section.
3. When I was having difficulty learning the material, I continued to review it.
4. I tried to monitor closely the areas I was having trouble remembering.
5. I noticed which material I was forgetting and focused on learning this information
6. I carefully determined what to study based on my memory of the material.

Motivation

1. I tried to learn as much as I could from this Excel course.
2. During training, I was motivated to learn the skills emphasized in the training program.
3. Learning the content covered in this training course is important to me.
4. I exerted considerable effort in this training course in order to learn the material.
5. During training, I attempted to improve my skills.
6. I attempted to learn the tasks taught during training.

APPENDIX F: ACT & SAT SCORES COMPARISON TABLES

ACT and SAT Score Comparison Tables developed by
 ACT. (2008, June). *Compare ACT & SAT Scores*. Retrieved from
<http://www.act.org/solutions/college-career-readiness/compare-act-sat/>.

Table 16. Concordance between ACT Composite Score and Sum of SAT Critical Reading and Mathematics Scores

SAT CR+M (Score Range)	ACT Composite Score	SAT CR+M (Single Score)
1600	36	1600
1540-1590	35	1560
1490-1530	34	1510
1440-1480	33	1460
1400-1430	32	1420
1360-1390	31	1380
1330-1350	30	1340
1290-1320	29	1300
1250-1280	28	1260
1210-1240	27	1220
1170-1200	26	1190
1130-1160	25	1150
1090-1120	24	1110
1050-1080	23	1070
1020-1040	22	1030
980-1010	21	990
940-970	20	950
900-930	19	910
860-890	18	870
820-850	17	830
770-810	16	790
720-760	15	740
670-710	14	690
620-660	13	640
560-610	12	590
510-550	11	530

Table 17. Concordance between ACT Combined English/Writing Score and SAT Writing Score

SAT Writing (Score Range)	ACT Composite Score	SAT Writing (Single Score)
800	36	800
800	35	800
770-790	34	770
730-760	33	740
710-720	32	720
690-700	31	690
660-680	30	670
640-650	29	650
620-630	28	630
610	27	610
590-600	26	590
570-580	25	570
550-560	24	550
530-540	23	530
510-520	22	510
480-500	21	490
470	20	470
450-460	19	450
430-440	18	430
410-420	17	420
390-400	16	400
380	15	380
360-370	14	360
340-350	13	340
320-330	12	330
300-310	11	310

APPENDIX G: 1600 AND 2400 SAT FORMAT COMPARISON TABLE

SAT Score Comparison Table developed by Anaheim Union High School District. (2014). A score comparison between the ACT, old SAT, and New SAT reasoning tests. Retrieved from <http://www.auhsd.us/view/2170.pdf>.

Table 18. A Score Comparison between the ACT, Old SAT, and New SAT Reasoning Tests

ACT	Old (pre-2005) SAT	New (Current) SAT Reasoning
36	1600	2400
35	1560-1590	2340
34	1510-1550	2260
33	1460-1500	2190
32	1410-1450	2130
31	1360-1400	2040
30	1320-1350	1980
29	1280-1310	1920
28	1240-1270	1860
27	1210-1230	1820
26	1170-1200	1760
25	1130-1160	1700
24	1090-1120	1650
23	1060-1080	1590
22	1020-1050	1530
21	980-1010	1500
20	940-970	1410
19	900-930	1350
18	860-890	1290
17	810-850	1210
16	760-800	1140
15	710-750	1060
14	660-700	1000
13	590-650	900
12	520-580	780
11	500-510	750

APPENDIX H: MANIPULATION CHECK

Manipulation check items

SCALE

[1 = Yes, 2 = No]

Manipulation Check

1. During training, I was periodically prompted to ask myself questions about my learning.
2. During training, I had to ask myself questions about the learning strategies I was using.
3. During training, I received questions that asked me about my learning progress.
4. After training, I was asked my opinions about technology.
5. After training, I received questions about technology.

APPENDIX I: UCF IRB LETTER



University of Central Florida Institutional Review Board
 Office of Research & Commercialization
 12201 Research Parkway, Suite 501
 Orlando, Florida 32826-3246
 Telephone: 407-823-2901 or 407-882-2276
www.research.ucf.edu/compliance/irb.html

Approval of Human Research

From: **UCF Institutional Review Board #1
FWA00000351, IRB00001138**

To: **Lauren Elise Benishek**

Date: **June 10, 2014**

Dear Researcher:

On 6/10/2014, the IRB approved the following human participant research until 6/9/2015 inclusive:

Type of Review: UCF Initial Review Submission Form
 Project Title: The Impact of Training Design and Individual Differences in
 Online Learning Systems
 Investigator: Lauren Elise Benishek
 IRB Number: SBE-14-10332
 Funding Agency:
 Grant Title:
 Research ID: N/A

The scientific merit of the research was considered during the IRB review. The Continuing Review Application must be submitted 30 days prior to the expiration date for studies that were previously expedited, and 60 days prior to the expiration date for research that was previously reviewed at a convened meeting. Do not make changes to the study (i.e., protocol, methodology, consent form, personnel, site, etc.) before obtaining IRB approval. A Modification Form **cannot** be used to extend the approval period of a study. All forms may be completed and submitted online at <https://iris.research.ucf.edu>.

If continuing review approval is not granted before the expiration date of 6/9/2015, approval of this research expires on that date. When you have completed your research, please submit a Study Closure request in iRIS so that IRB records will be accurate.

Use of the approved, stamped consent document(s) is required. The new form supersedes all previous versions, which are now invalid for further use. Only approved investigators (or other approved key study personnel) may solicit consent for research participation. Participants or their representatives must receive a copy of the consent form(s).

In the conduct of this research, you are responsible to follow the requirements of the Investigator Manual.

On behalf of Sophia Dziegielewski, Ph.D., L.C.S.W., UCF IRB Chair, this letter is signed by:

Signature applied by Joanne Muratori on 06/10/2014 12:26:29 PM EDT

IRB Coordinator

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