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Individual Differences and Usage of Learner Control

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INDIVIDUAL DIFFERENCES AND USAGE OF LEARNER CONTROL

by

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ABSTRACT

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Past learner control research has shown discrepant findings for hypothesized learning outcomes. In order to shed light on these inconsistent findings, this study investigated adult learners' use of learner control features in an online training program, and examined the usage in relation to individual differences. A sample of participants recruited from a crowdsourcing website was given a high level of learner control, and their progress was tracked as they completed an online Microsoft Excel training program. It was hypothesized that learner behavior during training partially mediated the relationship between individual differences and learning outcomes in a high learner control training environment. Results indicated that the relationship between cognitive ability and learning outcomes was partially mediated by the usage of learner control features. Hypotheses regarding other individual differences were generally unsupported, possibly due to the context of the study: a voluntary training program completed by adults who were compensated with a relatively small amount of money. Future research on learner control should be conducted on employee samples or in-person.

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CHAPTER I

INTRODUCTION

Training in organizations has remained a prevalent topic in research, technology advancement, and practice in Industrial and Organizational Psychology (DeRouin, Fritzsche, & Salas, 2004). According to the American Society for Training and Development's (2011) State of the Industry report, of over 400 U.S. organizations, $171.5 billion was spent on employee training in 2010 (Green & McGill, 2011). On average, organizations spent $1,228 per employee that year, each of whom spent an average of 32 hours in training. Of the various training methods utilized, 29% were technology-delivered (Green & McGill, 2011). This trend toward increasingly computer-based training is of significant concern, especially considering the relative lack of research on this shift and its potential impact on training expenditures and learning.

Arthur, Bennett, Edens, and Bell (2003) conducted a meta-analysis on the effect of training design, identifying training delivery method as playing an important role in overall training effectiveness. Specific training delivery methods were compared, including lecture, audiovisual, discussion, self-instruction, programmed instruction, and computer-assisted instruction. Sample-weighted mean difference scores of effect sizes for learning due to delivery method for cognitive skills ranged from .20 to 1.56. For interpersonal skills, mean differences ranged from .78 to 1.44 standard deviations. The authors noted a wide range of effect sizes with few consistent findings for delivery method across skill types. These results warrant a further exploration of which methods, and which features of those methods, influence the effectiveness of employee training.

Increasingly, organizations implement e-learning methods to train employees, in the hopes that this method will reduce monetary and time costs while maintaining strong learning outcomes. Brown (2005) defines e-learning as "the use of computers and networking technology for knowledge and skill building" (p. 465). This term describes instructional material accessed on an individual computer with the use of software as well as internet-based programs which can be accessed from any computer with a connection to the internet. The terminology is not universally agreed upon. Some researchers refer to online learning and e-learning interchangeably, others distinguish the two due to the source of the content of the training material, and still others distinguish between differences in their contexts, access, connectivity, and flexibility (Moore, Dickson-Deane, & Galyen, 2011). Because e-learning can be conceptualized as a broader term, encompassing all learning enhanced with electronic devices, the present thesis will focus on online learning specifically, which I will define as any training program delivered via the internet, accessible from any location with an available internet connection.

Online learning can provide numerous benefits to both employees and organizations. Employees can choose where and when is the most convenient to train, which may make it more efficient and cost-effective than traditional training approaches for many organizations (Bell & Kozlowski, 2010). Along with these organizational benefits, online learning can give trainees unprecedented control over their own learning process. The value of granting trainees control over the learning process, which is a training design feature called learner control, is widely debated, and evidence is mixed as to its effects. Some research has found that matching learners' preferred instruction style to mode of instruction provides no benefits (Cook, Thompson, Thompson, & Thomas,

2009; Hannafin & Sullivan, 1996; Pashler, McDaniel, Rohrer, & Bjork, 2009; Massa & Mayer, 2006), while others have found that matching preferences can provide learning benefits (Constantinidou & Baker, 2002; Freitag & Sullivan, 1995). Due to this controversy, it has been suggested there is a need for more fundamental research to "better understand what, how, and when" training works before making further broad conclusions (Salas & Cannon-Bowers, 2001, p.481).

Learner Control Defined

Users have different degrees of control in different online learning programs, and the types and degrees of control available can be conceptualized as continua. The creator of an online learning program chooses the extent to which a trainee's learning experience can be changed. At the "low" end of each continuum is program control. In training incorporating program control, trainees follow a predetermined path that was decided upon by the creator of the training program; all decisions about order of and exposure to content are in the hands of the software, and therefore the training designer (Hannafin, 1984; Kraiger & Jerden, 2007). On the other end of the continuum is learner control. In training incorporating learner control, trainees may customize certain aspects of their training experience.

Four types of learner control have been identified: pace, sequence, content, and advisory (Milheim & Martin, 1991; Tennyson, Park, & Christensen, 1985). In a recent meta-analysis, these four characteristics emerged as most commonly used in learner control programs (Kraiger & Jerden, 2007). Pace control enables learners to choose the pace of the training, which includes spending more time on sections of the learners' choosing (e.g., more difficult material), and spending less time on other sections (e.g.,

easier sections). Sequence control permits learners to navigate through training sections in the path of their choosing, which may include completing topics out of order. Content control allows learners to decide which topics to learn, and which assessments to take during training. Lastly, advisory control allows learners to consult computer-generated advice about their progress through training. Because of the easier customizability, online training programs offer an ideal platform for learner control.

Because of these adaptable features, learner control provides learners with the option to focus on only the topics that are most relevant to them, to proceed through the training in the order they feel is most beneficial, and to spend more or less time on certain topics as they see fit (DeRouin, Fritzsche, & Salas, 2004). However, research suggests that not all learners exert control over their training effectively. Some studies show that learning outcomes increase when certain individuals are given learner control (Kinzie, Sullivan, & Berdel, 1988; Shyu & Brown, 1992), while others show that learning outcomes may actually decrease for some individuals when more learner control is given (Hannafin & Sullivan, 1996; Pollock & Sullivan, 1990).

Kinzie, Sullivan, and Berdel (1988) found that eighth-graders using a computer-based program to learn about solar energy learned more when they were allowed to control more aspects of their instruction. Both groups received pace control, advisory control in the form of feedback, and practice questions. In the learner control condition, students were also given sequence control, which allowed them to revisit past material after answering practice questions incorrectly. An average of 35% of the material was revisited for those in the learner control condition. In the program control condition, students were required to revisit past material after answering a practice question

incorrectly. Total time spent on the program did not differ by condition, but participants in the learner control condition scored higher on the posttest than students in the program control group. The authors suggested that being given some ability to make learning choices may intrinsically motivate students to learn.

Similarly, Shyu and Brown (1992) studied the learning outcomes from a learner-controlled computer-based training program containing a series of videos teaching origami (Japanese paper folding), a topic in which all participants had no experience. Undergraduate students were randomly assigned to either a learner controlled or a program controlled version of training. The learner control group was provided with a menu of segments and a suggested path, but could navigate through the program in any order, and could repeat or stop any segments of their choosing. In the program control group, subjects could repeat only the current video segment as many times as they wanted, but could not go back to view past segments. The group given learner control scored higher on the completion of an origami figure, as rated by expert origami judges. This difference between mean group scores was statistically significant. The learner control group also spent more total time using the training program, but the groups did not differ in pre- or post-training self-efficacy or attitudes toward instruction. Shyu and Brown also attributed these findings toward intrinsic motivation, and suggested that learner control should be integrated wherever feasible into procedural learning tasks.

In Hannafin and Sullivan's (1996) study of high school students with no geometry experience, students participated in a computer-based geometry learning program, and researchers found no differences in learning outcomes between learner and program control training. Researchers measured the students' preference for amount of

instruction, and randomly assigned them to one of two conditions: a level of control matched their preference, or a level that opposed their preference. In the "lean" program version, participants were shown 180 screens, and could choose to add an additional 155 optional screens to their own training program. In the "full" program version, all 335 screens appeared (the same 180 screens and the 155 optional screens), and participants could choose to skip any of the 155 optional screens. Posttest scores did not differ significantly by full and lean versions, nor did posttest scores differ by study condition (matched or opposed to preference). Researchers considered a screen to be viewed when a participant remained on that screen for longer than one second, and students receiving the full version did view more optional screens, as the screens were automatically presented in the full condition. Students whose condition matched their preference chose to view significantly fewer screens than those unmatched. This is contradictory to past research on learning outcomes of adult employees; Freitag and Sullivan (1995) found a positive relationship between matching preferences for amount of instruction and learning outcomes for a sample of employees.

In a study of 152 seventh-graders, the relationship between learner control and types of practice questions was mixed (Pollock & Sullivan, 1990). Students were told that their achievement in a program about tarantulas would be included in their course grade for their science class. Groups were fully crossed by practice mode (recall and recognition), gender, and control (learner and program). All groups viewed all information screens, but the learner control group was able to skip four practice question sections that were mandatory for the program control group. The practice questions also included explanations for incorrect answers. Students in the learner control group opted

to complete an average of 3.14 out of four possible practice sections. Students in the program control group scored significantly higher on recognition items than those in the learner control group, but there were almost no differences between groups on recall items. Because the optional practice question sections contained additional information, this was a form of content control. Giving control over content may be an ineffective tool to promote learning for students.

A meta-analysis by Kraiger and Jerden (2007) examined 32 studies that compared learner control to program control. Overall, the authors concluded that training with learner control resulted in slightly higher learning outcomes in comparison to programs without learner control. However the corrected weighted average d statistic of .19 had a 95% credibility interval that included 0, suggesting that the true population correlation may be null. When broken down by subgroup, the authors did find positive and significant affects for learner control on learning in work-related tasks over educational tasks, and learners with no experience versus those with previous experience. In general, effect sizes for learner control on learning outcomes were quite small, though increase by publication date, suggesting that as online training programs become more advanced, learner control features may also become more effective. Hannafin (1984) first suggested that learner control does not provide benefits for all learners in all topics and situations, and the large variances found in the recent meta-analysis provide evidence for this. Kraiger and Jerden proposed that this may be due in part to many unknown variables within the trainees or training systems. With this in mind, they proposed a model of learner control in which learner control directly influences learning outcomes, learner affect, and attitudes. The relationships are moderated by training variables and learner

variables. This yet-untested model seeks to account for some of the unexplained variance in learning outcomes by including learner characteristics (locus of control, goal orientation, and self-regulatory skills), individual characteristics (experience, motivation, job requirements, and innate factors), and training characteristics (system capabilities, pedagogical models, and organizational culture) in a model of learner control.

Kraiger and Jerden's (2007) meta-analysis has been recently updated to include 51 studies of learner control, bringing the total sample size from 2,655 to 4,563 participants (Landers, Reddock, & Mogan, 2012). Again, researchers found the overall effect of learner control on learning was quite small, and did not reach statistical significance. Some moderating effects were found, however. When training programs enabled learners to skip content (exercising content control), learners had superior outcomes to those unable to skip content. When learners could add content, learner outcomes were poorer. This meta-analysis also found a larger effect on learning when pace control was present. No effects were found for sequence or advisory control.

A limitation to this stream of research is that the use of learner control is often assumed among learners to whom it is provided. Few of these studies directly examine behavior during training; accordingly, the extent to which learner control features are actually used is largely unknown. Because of this, it is unclear whether the learning outcomes are influenced by the option of having learner control or if they are influenced by actually modifying the training. Kraiger and Jerden (2007) hypothesize that the features of learner control are not equally salient to all learners. Thus, trainees may behave differently in response to the learner control options they are given. However, no empirical research has explored this possibility, so it is also conceivable that all learners

given learner control will use the training exactly as it is prepared, not deviating at all from learners with program control. Examining the behavior that learners display during training may help to explain the inconsistencies in previous research results.

Usage of learner control features. No research to this point has tracked, timed, and analyzed participants' every click through a training program to measure of the usage of learner control features when control is provided. When the use of learner control is too broadly measured, the variation between learners may be lost. When learner control training behavior is included, researchers typically measure total time spent on the training program or number of screens viewed, but not the time spent on each section or the order sections are completed. Learners who utilize learner control very differently may appear to be similar in the captured data, and any differences between their learning outcomes will remain unexplained. For example, many researchers assess learner choice by measuring time on task, which is the total amount of time spent in a training program (Kinzie, Sullivan, & Berdel, 1988; Shyu & Brown, 1992; Brown, 2001). This may be unwise, because total time on task is likely multidimensional, consisting of all learner behavior throughout a training program. For example, if one participant in a learner-controlled training program chose to skip an entire section but spent substantially more time on all other sections, that person's total time would be similar to another participant who did not control pacing but spent the same amount of time on every section. While a time on task measure does measure the usage of learner control, it likely also contains a great deal of construct-irrelevant variance.

Thus, in the current learner control literature, researchers have made an untested assumption that all individuals utilize control features in a similar way. However,

allowing a learner to exert control over a training program does not necessarily imply that they are actually exerting control. By explicitly measuring control-related behaviors for all types of control given, incremental variance in a learner control model can be explained.

Prior research capturing specific learner behavior during training and their effect on learning outcomes is limited. In one study of adult trainees, post-training performance was investigated for a study of 78 employees taking a learner-controlled online training program (Brown, 2001). The training program taught a problem-solving process important to the organization's goals. Learner behavior was measured by total time spent on the training program and number of optional practice activities completed. Trainees spent an average of 500.08 minutes (SD = 106.98) on the training and completed an average of 84% of the available practice questions (SD = 11%). Given the standard deviations associated with these means, there was substantial variability in the way the participants interacted with the training program, although the actual usage of specific learner control features given is unknown. Additionally, the leap was made from learner behavior during training to learner choices made during training with a 6-item off-task attention post-training measure, asking learners to recall their off-task attention during training. Although there is certainly value in measuring participants' perceptions of their past behavior, the assumption that this directly measures actual behavior or choices is questionable, due to the nature of self-reported measurement of this construct (i.e., memory and social desirability). Ideally, participants would be asked to report during training the reason why they are choosing to skip to the next section, or spend extra time on the current section. However, this experience would greatly differ from a typical

training experience, especially in additional time and cognitive load. Objective learner behavior during training has never been measured objectively, and including this may be a key insight into training outcomes.

At present, it is unclear which feature or features of learner control provided to participants benefit learning. No single study has separately examined the types of learner control, and no theory or taxonomy exists regarding which type should affect learning. Kraiger and Jerden's (2007) meta-analysis results indicate that pace and sequence control together show a positive relationship with learning, but content control shows no relationship with learning. However, Landers, Reddock, and Mogan's more recent (2012) meta-analytic results reveal that sequence and advisory control show no significant relationships to learning. Surprisingly, the ability to skip content had a significant, positive relationship to learning outcomes, though the ability to add content or skip *and* add content did not affect learning. Because rather small effect sizes have been reported when types of control are examined individually, an investigation of the use of the use of all three types of control is warranted. Therefore, the usage of learner control features will be defined as the amount of control a participant has exerted over all types of control given throughout the training program. This measured variable will be computed as a standardized mean score for the use of all types of control.

Individual Differences and the Usage of Learner Control Features

Certain individual differences may influence the way that learners interact with learner-controlled training programs, and may help to explain these discrepant learning outcomes. If so, it is in an organization's best interest to design the training geared toward those learners. Specifically, it would be beneficial for organizations to know

whether or not to implement learner control in an online training program, as it may be helpful or hurtful for learning outcomes of certain people. Before any recommendations can be made, programs with learner control should be studied in relation to individual differences and behavior during training. Several individual differences appear relevant to learner control effectiveness based upon prior research.

Gully and Chen (2010) outline a framework of relevant individual differences which include stable, "relatively enduring characteristics" that affect behavior during training (p.6). These differences include capabilities, demographics, personality traits, and interests and values. Consequently, more global distal individual differences were chosen to investigate for the current study; experience, personality, goal orientation, locus of control, and cognitive ability. Although arguably important, transient and malleable individual differences such as motivation and self-efficacy are not included in the current model in an effort to provide a generalizable framework of individual differences which should impact learning.

Experience with training content domain and learner control usage. Kraiger & Jerden (2007) found that, when given learner control, trainees with no prior experience with the training content outperformed trainees with some experience. This unintuitive finding may be explained by examining differences between actual usage of learner control features, based on experience level. Inexperienced learners may use every resource available to them and exhibit behavior during training that positively affects learning outcomes (e.g., viewing all content that is made available to them, in the order it is presented by the designer of the training program). This training experience closely resembles a training program with low learner control. In contrast, learners experienced

with the training material already may utilize control to spend less time on the training program in the interest of efficiency (i.e., not spending time on topics they already know) when they are given control over training (Shyu & Brown, 1992). Thus, task experience should predict the use of learner control.

Hypothesis 1a. Experience with the training content domain will positively predict the use of learner control features in training programs with learner control.

Big Five personality and learner control usage. Past research has shown that some of the Big Five personality traits are related to differences in how learners interact with training programs (Ones, Viswesvaran, & Dilchert, 2005). Neuroticism and agreeableness have been shown to have weak relationships with training outcomes, possibly due to non-linear relationships with performance (Barrick & Mount, 1991). Conscientiousness, openness to experience, and extraversion have been found to be consistently related to training proficiency (Barrick & Mount, 1991; Hough, 1992; Schmidt, Shaffer, & Oh, 2008). These relationships with training proficiency likely stem from differential behavior during training. Individuals that are high in conscientiousness tend to be planful, organized, hardworking, and persevering, and are more likely to achieve educational success (Barrick & Mount, 1991). Individuals that are high in openness tend to be creative and curious, and as a result are more likely to be active than passive in training (Goldberg, 1993; Barrick & Mount, 1991). Individuals high in extraversion, specifically ambition, initiative, and surgency, are more likely to use more features of training programs (Goldberg, 1993). Therefore, differences in these personality traits should influence behavior during learner-controlled training. Individuals high in openness, conscientiousness, and extraversion should use more

learner control features when they are available because of their increased tendency for being active during learning and showing initiative.

Hypothesis 1b. Trainee openness will positively predict the use of learner control features in training programs with learner control.

Hypothesis 1c. Trainee conscientiousness will positively predict the use of learner control features in training programs with learner control.

Hypothesis 1d. Trainee extraversion will positively predict the use of learner control features in training programs with learner control.

Mastery goal orientation and learner control usage. Goal orientation is a framework to describe differences in interpretation, experiences, and responses to achievement situations (Dweck, 1986; Nicholls, Cheung, Lauer, & Patashnick, 1989). At its inception, goal orientation was considered a two-dimensional construct: learning (mastery) goal orientation and performance goal orientation. The foundation of the two constructs lay in differing beliefs about achievement: a learner's desire to understand the learning material or a learner's desire to be evaluated as superior. Those with a learning goal orientation focus upon understanding the material. Those with a performance goal orientation focus upon demonstrating superiority of their own test-taking skill and ability over others (Nicholls, et al., 1989).

Recently, proponents of a three dimensional construct argue that performance goal orientation should be separated into performance-prove and performance-avoid (Brett & VandeWalle, 1999; Elliot & Church, 1997; Porath & Bateman, 2006). In this three dimensional construct, mastery orientation refers to individuals who increase effort and persistence in achievement situations, employ "solution-oriented self-instruction",

and believe that abilities are malleable (Brett & VandeWalle, 1999, p. 865). These individuals are more likely to seek feedback to gather information, and be proactive to enhance their own learning (Porath & Batemen, 2006). In a two-dimensional goal orientation construct, performance goal orientation includes both a desire for favorable judgments and a desire to avoid unfavorable judgments (Brett & VandeWalle, 1999). In a three-dimensional construct, individuals with a performance-prove goal orientation focus on performance, and believe abilities are rigid attributes; increasing effort would point out low ability, so emphasis is placed on appearing more competent than others in areas which they are competent (Brett & VandeWalle, 1999; Pintrich, 2000). Individuals high in performance-avoid goal orientation are also concerned with performance, but they are characterized as attempting to avoid negative evaluations and employing defensive behavior in order to avoid seeming incompetent (Button, Matthieu, & Zajac, 1996). This may result in a "maladaptive pattern of helplessness" in learning or achievement situations (Porath & Batemen, 2006, p. 186).

Goal orientation contributes to variability in what learners will attend to in training and how they will interact with training features. Button, Matthieu, and Zajac (1996) found that individuals high in mastery orientation are more focused when attempting to understand novel material or develop competence in training. A similar effect should be found in training programs that offer a high level of learner control; those high in mastery goal orientation should use more features of learner control to increase their exposure to new or difficult content while also decreasing their exposure to familiar or easier content.

Hypothesis 1e. Mastery goal orientation will positively predict the use of learner control features in training programs with learner control.

Locus of control and learner control usage. Locus of control refers to the tendency to attribute consequences of behavior to either internal or external causes (Collins, 1974). Rotter (1966) originally defined external locus of control as perceiving life events as not completely contingent upon a person's own actions, but rather as "the result of luck, chance, fate, as under the control of powerful others, or as unpredictable" (p.1). Individuals with internal locus of control interpret life events as contingent upon a person's "own behavior" or their "own relatively permanent characteristics" (p.1). Individuals high in internal locus of control tend to seek situations in which control is possible, exhibit better learning, pursue information actively, and are more likely to control or manipulate their surroundings than individuals high in external control (Spector, 1982). Empirical research has supported this theory. Kabanoff and O'Brien (1980) found that those high in internal control are more likely to choose leisure activities that allow more personal control. In a laboratory experiment of behavior in a competitive two-person game, participants were permitted to rely on their opponent or on themselves to score points (Julian & Katz, 1968). Individuals high in external control were more likely to rely on their opponent, and high internal control individuals were more likely to rely on themselves, even when the opponent might have earned more points.

Based on the locus of control literature, Spector (1982) asserted that employees higher in internal control are expected to exert more effort in situations in which they have more control. This is because those high in internal control are more likely to look internally for direction, whereas high external individuals are more likely to look to

others for direction. In fact, those high in internal locus have been shown to exert more effort during training because they are more likely to seek control over their learning environment, Noe and Schmitt (1986) report that internal locus of control positively related to self-reports of within-training exploratory behavior. Similarly, Lied and Pritchard (1976) found that internal locus of control correlated with self and trainer ratings of effort in an Air Force training program. Because locus of control relates to constructs salient to employee behavior in training, this is an important variable to include in an examination of the extent that learners use learner control features in online training. Internal locus of control should positively impact the extant that learners utilize control.

Hypothesis 1f. Internal locus of control will positively predict the use of learner control features in training programs with learner control.

Cognitive ability. Cognitive ability is a "very general mental capability that...involves the ability to reason, plan, solve problems, think abstractly, comprehend complex ideas, learn quickly, and learn from experience" (Gottfredson, 1997, p.13). The impact of general cognitive ability on learning is widely supported by meta-analyses in several contexts, including graduate education (Kuncel, Hezlett, & Ones, 2001), lab studies of skill acquisition (Ackerman, 1987), and on-the-job training performance (Schmidt, 2002). Because of its strong impact on learning outcomes in a wide variety of settings, it should certainly be explored in relation to behavior during the learning process.

Research shows that cognitive ability predicts not only learning and performance outcomes, but is correlated with constructs that should impact behavior before learning is

even assessed. Several of these correlates are relevant to behavior in an online learning environment with a high level of learner control. These correlates include physiological constructs such as the ability to perceive brief stimuli, neural processing speed, and motor skills (Ree & Carretta, 2002). Online training programs present stimuli (learning material) that must be perceived and processed by the learner while simultaneously progressing though the training program by physically moving and clicking a mouse. Because each of these constructs is positively related to cognitive ability, those higher in cognitive ability should be able to interact more with features of learner control in online training.

Hypothesis 1g. Cognitive ability will positively predict the use of learner control features in training programs with learner control.

Learner Control Usage and Learning Outcomes

Much of the past research on learner control compares learning outcomes between program and learner control groups; however, few researchers have studied the behavior that learners display during training enabled by learner control and the ultimate impact of their behavior on learning. Kraiger and Jerden (2007) hypothesize that the features of learner control are not equally salient to all learners. Thus, trainees may respond differently to the learner control features they are given. Because participant behavior has only been measured very broadly, deviation from program control may have gone undetected by researchers, although it may be an important influence on learning outcomes.

Learning outcomes. In Kraiger and Jerden's (2007) meta-analysis, learner control studies were coded as having procedural or declarative learning outcomes. The

authors argued that they found different effects of learner control by outcome. However, the differences they found were not statistically significant from each other. Campbell and Kuncel (2002) argue that a breakdown between declarative and procedural knowledge is not a useful distinction in training, because the two are difficult to separate in practice. Instead, they argue that "knowledge" and "skill" better describe the hierarchical learning outcomes that current assessment tools can distinguish between. Increases in knowledge could include labels, facts, rules or procedures, plans and goals. An increase in observable skill would be applying that knowledge to solve a problem or accomplish a goal (Campbell & Kuncel, 2002).

A critical feature of training design is that the training program should allow or induce the learner to actively create the knowledge or skill being trained (Campbell & Kuncel, 2002). If the features of learner control are used as a means to motivate the learner to actively produce the capability being trained, then using learner control should lead to improved learning. Support for this can be found in the learner motivation and active learning literature. Colquitt, LePine, and Noe (2000) found in their meta-analysis that motivation to learn positively predicts increases in both knowledge and skill, and explained incremental variance in both outcomes beyond the effects of cognitive ability. According to Bell and Kozlowski (2010), active learning "provides individuals with significant control over their learning" and that inducing active learning is associated with more positive learning outcomes (p. 265). Therefore, if motivation and active learning are indicated by increased usage of learner control, learning should be higher for those learners that choose to use learner control features.

Theoretically, the usage of each type of learner control should indicate a greater degree of motivation and active learning. The utilization of sequence control indicates that the learner is actively participating in the format of the training program. Utilizing pace control indicates that a learner is spending more time on more difficult or unfamiliar topics, or is spending less time on easier or familiar topics. Utilizing content control to skip sections that the learner already knows or add learning material when a topic is interesting or difficult, should also increase learning. It may seem counterintuitive that spending less time or viewing less content will predict higher learning outcomes; however, in Landers, Reddock, and Mogan's (2012) meta-analysis of learner control, studies of learner control with the option to skip content produced stronger, more positive effects on learning when compared to studies with the option to view more content or both skip and view more content. A possible explanation for this may be that viewing more information than necessary may cognitively exhaust a learner. Overall, exerting greater control over learner control features should result in increased learning outcomes. As previously discussed, few studies examine the extent to which learners actually utilize learner control features during training. When learner behavior was examined broadly, significant incremental variability in learning was explained above pre-training motivation (Brown, 2001). Together, time spent training and number of optional practice activities explained an additional 15% of the variance in posttest knowledge scores over pretest knowledge (Brown, 2001). This suggests that the utilization of certain learner control features during training should predict learning outcomes. Being able to utilize control over a training program should enable a learner to customize their training

experience to their specific learning preferences. Thus, learners that do exert control over a training program should learn more.

Hypothesis 2. The usage of learner control features will positively predict learning outcomes.

Usage of Learner Control Features as Mediator

The relationship between learner control and learning outcomes varies widely in the current research literature. Having a high level of learner control in a training program has led to poorer, equal, and superior learning outcomes in different studies. A viable explanation for these discrepant findings may be that researchers studying learner control have largely neglected to include individual differences relevant to both training contexts and learner control. Past research indicates that that there are distinct relationships between certain individual differences and learning outcomes in training situations (Colquitt, LePine, & Noe, 2000; Gully & Chen, 2010). Previously, Noe (1986) argued that individual attributes such as locus of control, motivation, and attitudes are crucial factors in the effectiveness of training. In a meta-analysis of training motivation, Colquitt, LePine, and Noe (2000) found that individual characteristics (e.g., personality, locus of control, and cognitive ability) significantly predict behavioral and learning outcomes in training. The authors theorize that these individual differences broadly affect pre-training motivation, behavior exhibited during training, and performance after training. There is no compelling reason to exclude learner behavior exhibited during training from this model; however, this has been ignored in the current learner control literature.

More recently, Gully and Chen (2010) agree that this still holds true; most empirical studies incorporate few, if any, individual characteristics into their theoretical frameworks. Therefore, little evidence exists to help understand how individual differences promote learning in which circumstances. Gully and Chen (2010) propose that studying training effectiveness in an Attribute-Treatment Interactions (ATI) framework will provide a deeper understanding of training design effectiveness. In an ATI framework, certain training delivery systems and designs may only be effective for some individuals, depending on their specific characteristics (Gully & Chen, 2010). Instead of determining whether a specific training design is or is not effective, a more critical goal is to determine which aspects of a training environment will allow optimum training outcomes for which individuals.

Gully and Chen's (2010) proposed ATI model posits that the relationship between individual differences and learning is mediated by intervening mechanisms, which include several cognitive processes such as information-processing, emotion regulation, attentional focus and effort allocation. The relationship between trainee characteristics and learning outcomes is also moderated by treatments, training design features, and situational characteristics. Learner control can be considered a training design feature because the creator of the program decides upon the types and level of learner control a training program will provide to the learner, and this will be consistent across all learners. However, the *usage* of learner control should not be considered a feature of training design because it is likely that learners engage in dissimilar behaviors when learner control is given. The usage of learner control should instead indicate varying levels of those intervening mechanisms (e.g., attention and effort allocation), a mediator in the

individual differences and learning relationship. Thus, the usage of learner control will be tested as a mediator in the relationship between individual differences and learning.

A moderating relationship is not predicted, because individual differences have been shown to directly predict learning in typical training programs with very low levels of learner control, or none at all (Schmidt, Shaffer, & Oh, 2008). The use of learner control features should not change the direction or strength of the relationship between individual differences and learning, but instead should partially explain why certain individuals learn more. Although the distal individual differences proposed in the model should directly predict learning outcomes, behavior during training resulting from those individual differences likely explains a portion of that relationship. If a learner does not exert control over features in training program, that learner experiences the same content as a learner without control, leaving only the broad effect of individual differences as predictors of learning. Thus, partial mediational relationships are proposed: individual differences predict training outcomes, but this relationship is partially mediated by the usage of learner control features. In the following sections, the specific mediation implied by each training-relevant individual difference will be discussed.

Experience with training content domain. As previously mentioned, Shyu and Brown (1992) found differences in procedural learning outcomes between a learner control group and a program control group in a sample of undergraduates with no previous task experience (origami). Learners with no experience learned more when given learner control. Similarly, Kraiger and Jerden found in their 2007 meta-analysis that learners with no experience in the training content learn more. These findings in a learner control context stand in direct opposition to previous computer training research.

Prior experience using software on computers has been shown to positively predict learning in a variety of software training programs (Gist, Schwoerer & Rosen, 1989; Martocchio & Webster, 1992; Webster & Martocchio, 1995). Gist et al., (1999) measured pre-training computer experience by the number of years using computers before a training program for a financial software program. Experience positively and significantly correlated with post-test performance at r = .38. Martocchio and Webster (1992) measured computer experience with five self-rated items regarding computer skills, experience, typing skills, and computer usage. Computer experience positively and significantly predicted learning after completing a training program on the use of WordPerfect, and accounted for 8% of the variance in learning. Similarly, Webster and Martocchio (1995) measured pre-training experience specific to the usage of a Macintosh construction software program taught during training. Experience with that program and similar programs positively and significantly predicted learning in an SEM model (standardized direct effect was .21).

The discrepancy of the findings for the relationship between experience and learning may be partially explained by the mediating role of learner behavior. Experience level should affect learning outcomes directly but should also affect how much control learners exert during training. If more experienced learners utilize more learner control features in the interest of efficiency as hypothesized, this should lighten the cognitive load of training. Working memory is negatively affected by extraneous cognitive load, which may include material an experienced trainee is already familiar with (Sweller, vanMerrienboer, & Paas, 1998). If the use of control allows learners to spend less time on or skip sections in which they are already familiar, this should

positively affect learning outcomes. Thus, including learner behavior in the hypothesized model should explain more variability in learning outcomes.

Hypothesis 3a. The relationship between experience and learning outcomes will be partially mediated by the use of learner control features.

Big Five personality. Personality has only recently been studied in the context of learner control research, but this preliminary research supports that certain personality traits influence the relationship between learner control and training performance. Individuals high on both of these traits exhibited better performance in a high learner control training condition, while those individuals low in openness and extraversion exhibited better performance in low learner control (Orvis, Brusso, Wasserman, & Fisher, 2011). Conscientiousness was not found to significantly interact with learner control, nor did it directly predict performance, but the authors speculated that the short length and low complexity of their particular training program did not allow sufficient opportunity to display behaviors related to conscientiousness such as perseverance and planning. Small effect sizes were reported for all three personality traits to predict learning outcomes for learner control (Orvis, et al., 2011). This may be because these traits directly relate to learning outcomes, and additionally affect learning through the usage of learner control features, which was unmeasured. More variability in learning outcomes may be explained by the effect of personality through behavior in training. For example, a learner high in any of these traits is already more likely to have higher learning outcomes. But because the learner is likely to interact with a training program more than a learner low in those traits, as measured by the use of learner control features, those different actions should help explain the increase in their learning outcomes.

Hypothesis 3b. The relationship between openness and learning outcomes will be partially mediated by the use of learner control features.

Hypothesis 3c. The relationship between conscientiousness and learning outcomes will be partially mediated by the use of learner control features.

Hypothesis 3d. The relationship between extraversion and learning outcomes will be partially mediated by the use of learner control features.

Mastery goal orientation. Findings from past training research suggest that mastery goal orientation should affect learning outcomes directly and through behavior displayed in training (Button, Matthieu, & Zajac, 1996; Porath & Bateman, 2006). Meta-analytic results also show that mastery goal orientation is positively related to learning (Payne, Youngcourt, & Beaubien, 2007). However, these findings do not consistently transfer to a learner control context. In a study of undergraduate students, Schmidt and Ford (2003), found that mastery orientation positively related to skill-based but had no relationship to declarative knowledge. In a sample of employees taking a high learner control training program, Brown (2001) found that those high in mastery orientation had unexpectedly lower learning outcomes, and that mastery orientation had a significantly negative relationship with the number of optional practice questions competed during training. However, mastery orientation had a significantly negative relationship with self-reported off-task attention. Brown (2001) speculated that because the employees were told that they would have access to the training material after the study, those high in MGO may have become familiar with the process as a whole, spent less time training and learning at their first introduction to training, and planned on using the training more

afterward. He also suggests that the effects of MGO on learning may be mediated by behavior during training (Brown, 2001).

Following Brown's (2001) suggestion for a mediating model, it is possible that learners high in MGO were using more learner control features, but planned to learn more over time, not in just the first single session. Although MGO was negatively correlated with practice activities, this could actually indicate a form of content control; skipping exposure to content by completing fewer optional practice activities. Including the usage of all three types of learner control as a mediator between MGO and learning likely explains more variance in learning outcomes, especially in a training program in which participants will be unable to return to the training materials. Thus, learners high mastery goal orientation should utilize more features of learner control during the training program in the current study in order to increase their knowledge in the content of the training course, which will ultimately increase learning outcomes.

Hypothesis 3e. The relationship between mastery goal orientation and learning outcomes will be partially mediated by the use of learner control features.

Locus of control. Spector (1982) suggested that performance in training could be predicted by locus of control in situations where control can be attempted by the trainee. This belief has been supported empirically in studies of job performance, based on the theory that those higher in internal locus of control are more likely to believe that performance is the result of personal efforts. In a study of naval personnel, employees high in internal control scored higher on both effort and performance (Broedling, 1975). Meta-analytic evidence also supports that internal locus of control is positively correlated with job performance (Judge & Bono, 2001). Because those high in internal locus should

also be more likely to believe that learning is based on their own personal control and effort, these findings from job performance should transfer to training performance both directly and through behavior during training. Researchers in education have found that website usage and locus of control correlate positively with course grades. In a study examining the predictors of class performance in a Web-based undergraduate Statistical Methods in Psychology course, Wang and Newlin (2000) found that those who used the course website more frequently (e.g.., logged in, read posts, wrote posts) and those higher in internal locus performed better in the class overall. Though correlations between website usage and locus of control were not reported, it is possible that those higher in internal locus were more likely to be using features of the website more frequently, and this in turn increased class performance.

In a learner control training context, locus of control has only been measured in one study examining learning outcomes, which did not measure learner behavior in training (Chang & Ho, 2009). Locus of control was measured for two classes of college freshmen. One class was given program control and the other was given learner control online language learning programs to complete. The learner control group scored better than the program control group on the posttest, but locus of control did not directly predict learning outcomes (Chang & Ho, 2009). However, this lack of prediction may be due to its measurement. Locus of control was assessed by an adapted questionnaire regarding locus of control for academic responsibility, and participant locus of control was dichotomized into internal or external locus labels rather than examining locus of control as a continuum.

With better measurement of locus of control, previous theory and empirical evidence suggest a direct relationship should emerge. More critically, this relationship should be mediated by behavior in training, because learners high in internal locus should attribute learning to their own behavior, and thus be more likely to use the features provided in a training program.

Hypothesis 3f. The relationship between locus of control and learning outcomes will be partially mediated by the use of learner control features.

Cognitive ability. A large body of research supports the claim that general intelligence predicts learning. Kuncel, Hezlett and Ones (2004) go so far as to claim that cognitive ability is a "universal predictor of job training success" (p. 149). A multitude of individual studies as well as meta-analytic evidence indicate that cognitive ability positively and strongly influences knowledge and skill acquisition (Colquitt, LePine, & Noe, 2000; Hunter & Hunter, 1984; Ree & Earles, 1991). Based on previous research in the area, Colquitt, LePine and Noe (2000) conclude that the reason cognitive ability is such a large influence on learning is based in differences in information processing capacity. An online training environment is a perfect example of a situation in which differences in information processing capacity should emerge. Any online training program contains an abundance of information that must be recalled later. Cognitive load should be increased further when trainees are given control over the pace, sequence, and content of the information. Not only should those higher in cognitive ability be more equipped to use control, but they should also benefit the most from using control because of increased information processing capacity. Because those higher in cognitive ability have higher information processing capacity, they should be able to learn more quickly

both based on differences in cognitive ability but also in an increased ability to utilize control.

Hypothesis 3g. The relationship between cognitive ability and learning outcomes will be partially mediated by the use of learner control features.

The Present Study

The hypotheses described above are depicted in Figure 1. The purpose of this study is to test this model when learner control is present. Past learner control research has shown discrepant findings for hypothesized learning outcomes. This study is the first to examine adult learners' use of learner control features in detail, and look at those learner behaviors in relation to individual differences and learning outcomes.

In the current study, all participants were given a high level of learner control, and their progress was tracked as they completed an online Microsoft Excel training program. Learners had pace control, content control, and sequence control. The usage of learner control was measured individually for each type of control; the exertion of pace, content, and sequence control, and the extent to which each is exerted. If pace control was exerted, the participant may have been spending more time or less time than other participants in each section. If content control was exerted, the participant may have been viewing more or less content during the training program. The exertion of sequence control was measured by use of navigational buttons. Pre-training knowledge was measured to serve as a control variable in order to account for inter-individual variation not due to learner behavior. Learning outcomes were measured by performance on two posttests: one measuring knowledge about Microsoft Excel and one measuring skills in Microsoft Excel. This study used a sample of participants recruited from a

crowdsourcing website. It was hypothesized that learner choices partially mediate the relationship between individual differences and learning outcomes in a high learner control context.

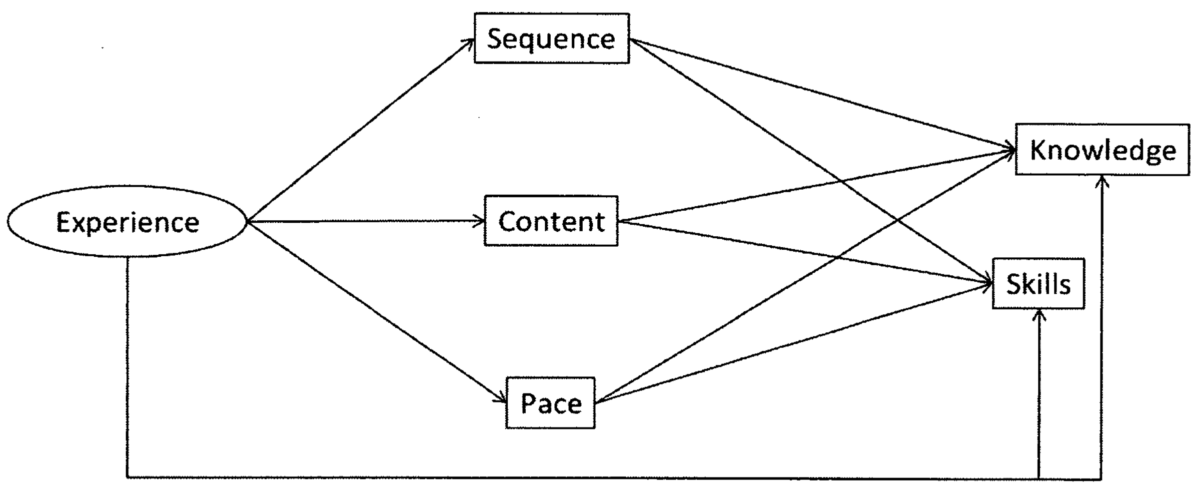

Figure 1. Proposed model of experience and learner control usage.

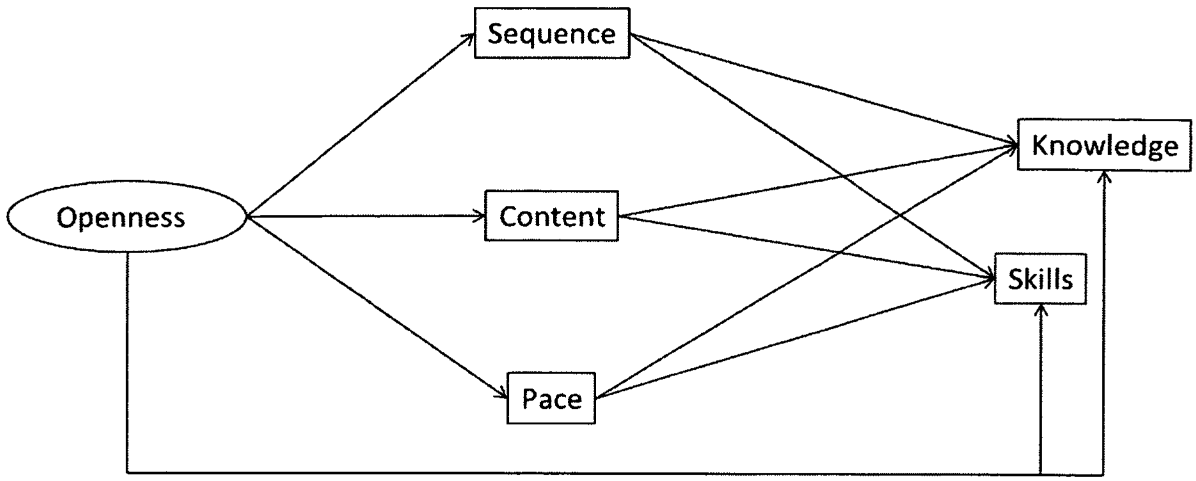

Figure 2. *Proposed model of openness and learner control usage.*

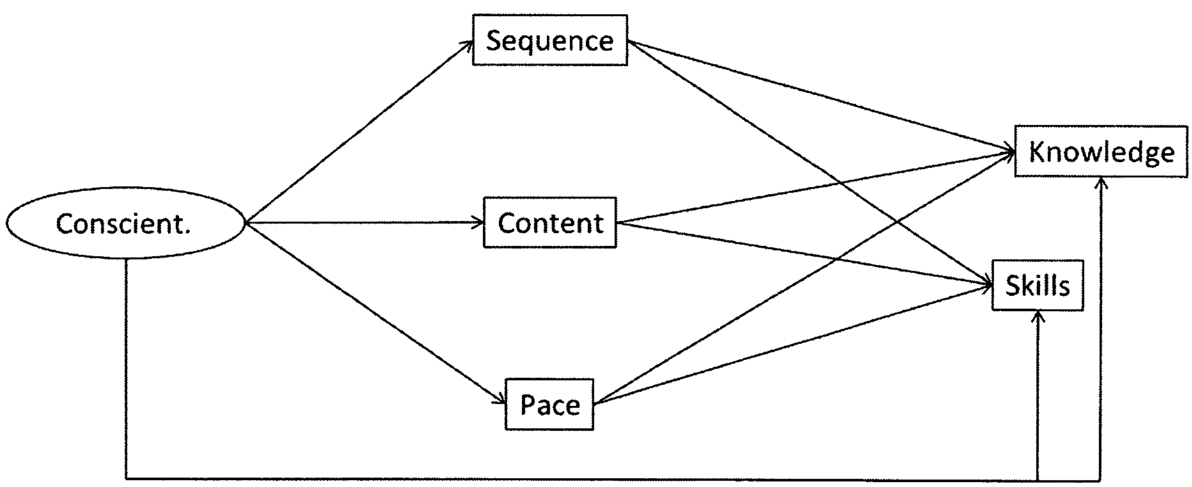

Figure 3. *Proposed model of conscientiousness and learner control usage.*

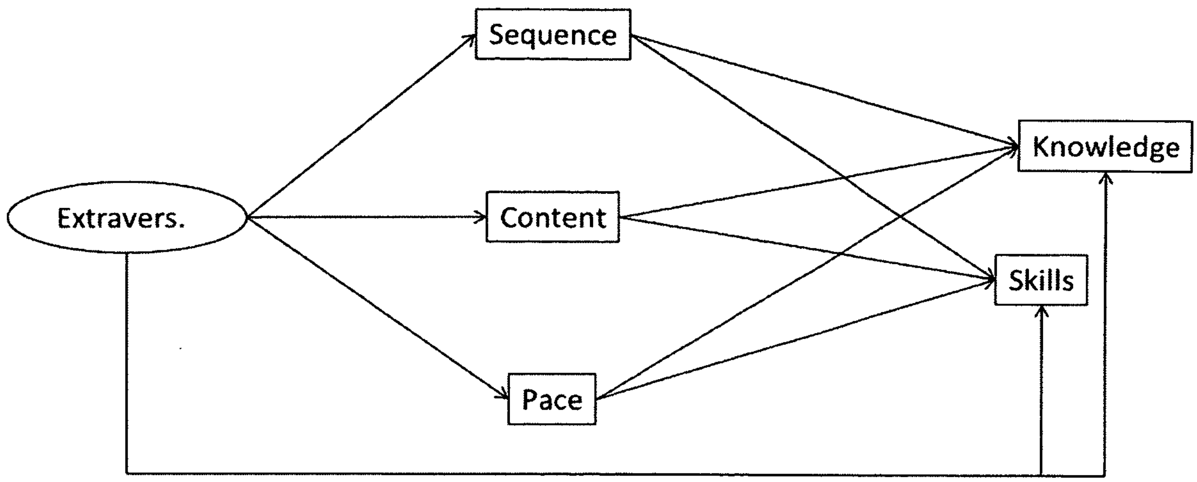

Figure 4. *Proposed model of extraversion and learner control usage.*

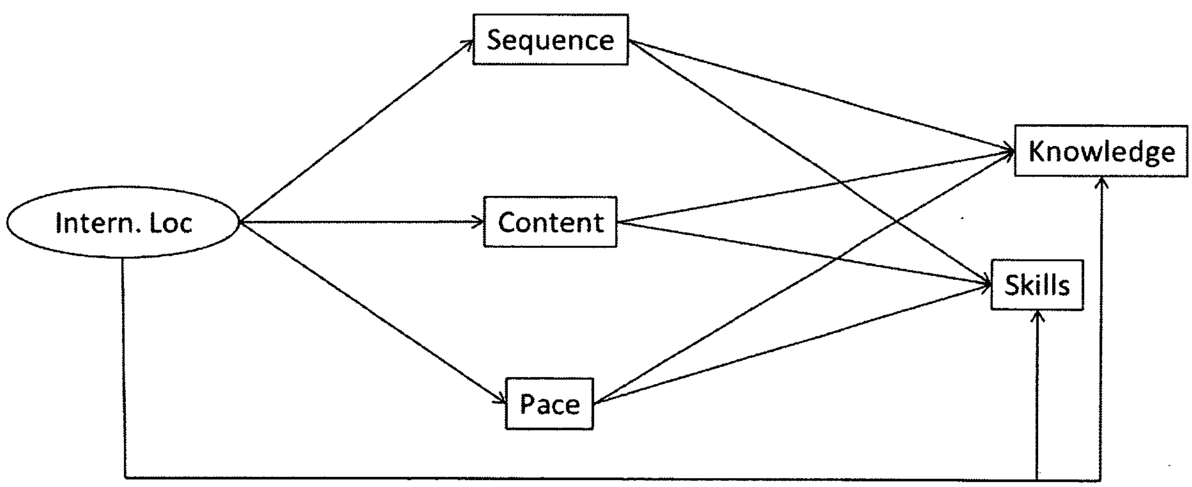

Figure 5. *Proposed model of internal locus and learner control usage.*

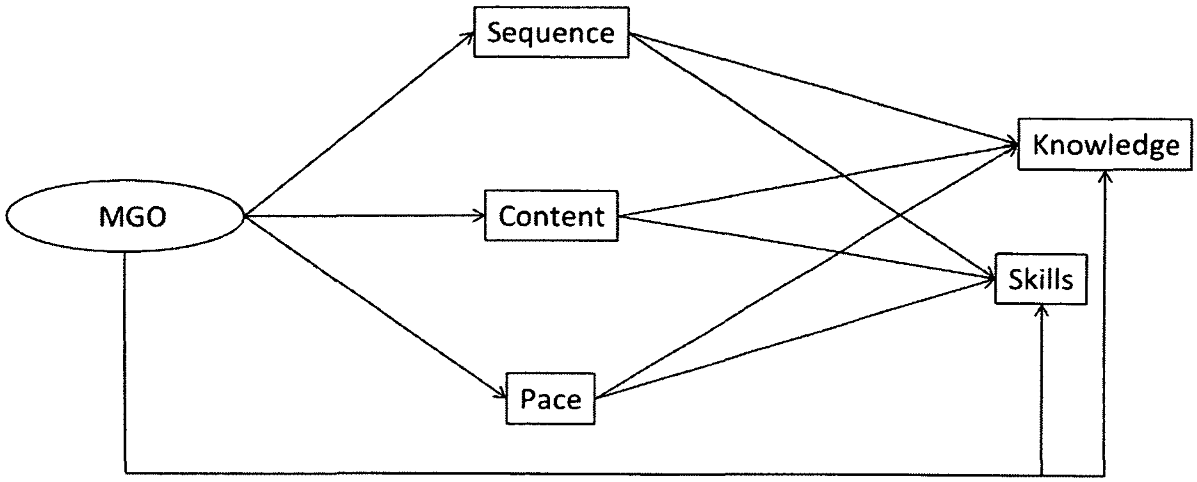

Figure 6. *Proposed model of MGO and learner control usage.*

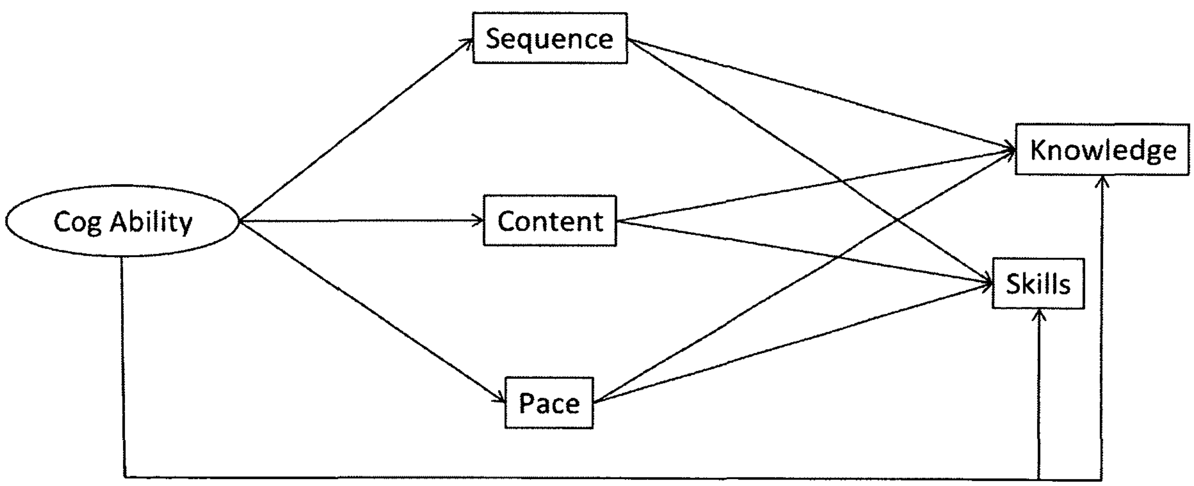

Figure 7. *Proposed model of cognitive ability and learner control usage.*

CHAPTER II

PILOT STUDY

Learner control has not been studied extensively in working adult samples, and it is unclear how well findings from adolescent and undergraduate students will generalize to working adults. Past research shows that adult learners and children may learn differently (Kuhn & Pease, 2006). This finding causes uncertainty about the generalizability of using younger student populations, including many of the studies found in Kraiger and Jerden's (2007) meta-analysis. Kraiger and Jerden conclude that learner control is more effective in learning work-related topics than educational topics but support this with a very small work-related sample. Additionally, the authors suggest that gains in learning due to learner control occur because learner control allows motivated learners to customize their own learning experience to accomplish specific goals. Employees may be more likely than students to be motivated if skills learned in training will directly apply to their job. Brown and Ford (2002) further attest that workplace learning is different from educational learning because employees need rapid, on-demand training that is easily accessed from different locations, and focuses on specific material for immediate job application. Based on the differences between employee and student learning, an alternative solution to studying learner control is proposed.

A contemporary internet phenomenon called crowdsourcing has already been utilized for organizational purposes but may also allow access to a viable sample of working adults for research. Broadly defined, crowdsourcing is the "outsourcing of tasks to the general internet public" (Kleemann, Vob, & Reider, 2008, p. 5). Organizations

have used crowdsourcing as an alternative to hiring temporary employees for a wide range of purposes. The most common purposes are consumer product development, design and configuration, specifically defined tasks, open calls, and consumer profiling, product rating. Notable examples of soliciting work through crowdsourcing include input on Fiat car design, idea generation for new Dell technologies, and open calls for community and amateur news reporting for local and national newscasts and websites (Kleemann, Vob, & Reider, 2008). Recently, social science researchers have looked to crowdsourcing for participant recruitment. Operationally defined for research, crowdsourcing is "the paid recruitment of an online, independent global workforce for the objective of working on a specifically defined task or set of tasks" (Behrend, Sharek, Meade, & Wiebe, 2011, p. 801). Although crowdsourcing has only recently started to be used as a means for research, early evidence suggests that it may be a viable approach to recruit participants and collect data for social science research (Behrend et al., 2011).

Generally, participant samples recruited from the internet allow researchers to access a broader and more diverse group of people than undergraduate students (Dandurand, Shultz, & Onishi, 2008), and it seems that this may also hold true for crowdsourcing websites. Research has shown that participants recruited from crowdsourcing websites are somewhat similar to those recruited from undergraduate Psychology research pools. Both populations are motivated primarily by extrinsic factors: minimal financial compensation for crowdsourced participants and course credit for undergraduate participants. Effect sizes for differential functioning of Big Five personality and goal orientation items were found to be quite small. However, the populations differ in other areas. In an empirical study comparing undergraduate

participants to crowdsourcing participants, crowdsourced participants were found to better generalize to employee populations because they were more representative of working adult population than undergraduates. They were more likely to be employed, have relevant work experience in a career-oriented job, and were also more ethnically diverse (Behrend et al., 2011). Amazon Mechanical Turk (mTurk) is the most well-known crowdsourcing website (Kleeman, Vob, & Reider, 2008). It is a self-proclaimed "marketplace for work" (Amazon, 2011). "Requestors" create a job request, which includes a title, task description, relevant keywords, compensation amount for task completion (typically between $0.01 and $13.00), how many "Workers" are needed, the expiration, and amount of time before the task completion will be approved. The Requestor can also filter the job request to specific Workers by country location and approval rate, which reflects a worker's quality on previous tasks according to Requestors. Workers sign up to complete these job requests or "Human Intelligence Tasks" (HITs) at their convenience. Individuals 18 years and older can sign up for a free Worker account, allowing access to view and participate in HITs. Each worker is only allowed one account. To make sure of this, an alphanumeric worker ID tracks performance and payment records, allowing reasonable certainty that a Worker will only complete a HIT once. Tasks are completed in exchange for pre-determined financial compensation. If the task is not completed sufficiently, the Requester may choose to reject the work and not pay the worker, which will be reflected in a lower approval rating for the Worker and also negatively affect Requestor statistics.

Researchers have begun using mTurk to recruit participants for research in psychology (e.g. Sharek, 2010; Cole, et al., 2009), but concerns remain regarding the

viability of the data collected from Turk Workers. Though initial research seems promising about the viability of mTurk workers as research participants, there are risks and possible downsides. Behrend and colleagues (2011) found that data from mTurk workers and undergraduates did not significantly differ in completeness or quality, study completion time, or word count of open-ended questions. However, mTurk workers were significantly higher in social desirability scores, internet knowledge, and computer knowledge and experience. More empirical studies using crowdsourced workers are needed in order to best utilize crowdsourcing tools for research, and this study will also contribute to our understanding of such samples. Thus, a three-part pilot study was conducted in order to examine relevant variables and potential issues with participation data collected from Amazon Mechanical Turk. This was done with the purpose of answering three questions before conducting the main study. First, do learning outcomes vary sufficiently in an mTurk sample to allow modeling of that variance? Second, do mean differences exist between undergraduate and mTurk samples on key study variables? Third, does the degree of monetary incentive influence mTurk participation levels?

Method

Participants. A power analysis was conducted for the pilot study using a computer program, G*Power 3 (Faul, Erdfelder, Lang, & Buchner, 2007). Using an a priori one-way ANOVA for three groups, with an alpha level of .05 and power of .95, the power analysis indicated that a sample of 46 participants would be required to find an effect. In order to account for poor quality or missing data, data were collected from 59 participants. Data collected from mTurk participants were also compared to data from a

sample of 40 undergraduates which was collected for a separate study using the same training materials (Callan & Landers, 2012).

Frequencies for pilot participant characteristics can be found in Table 1. Inspection of these frequencies allowed insight into who signed up for the study on mTurk. The majority of participants were Caucasian (81.4%) and female (61.0%). Most participants reported attending school post high school; 30.5% had completed some college, 11.9% obtained an Associate's degree, and 30.5% obtained a Bachelor's degree. Most mTurk Workers reported they were not currently enrolled in school (76.3%), but most were employed (71.2%). Additionally, mTurk Workers reported an average age of 33.86 years (SD = 10.02).

Materials. The Microsoft Excel training program used in this pilot study was adapted from a training program created for training research and has been used in several research studies investigating self-regulation and computer-based training programs (Sitzmann, 2012; Sitzmann & Johnson, 2012; Sitzmann & Ely, 2010; Sitzmann, Ely, Bell, & Bauer, 2010). The original materials consisted of a four-hour program comprised of four modules with three topics each, and contained terms and visual representations (screenshots of Microsoft Excel) at each step. This training program was converted into an online format and reduced to one hour for use in another study of learner control (Callan & Landers, 2012). The one hour training includes one topic from each of the four modules (see Appendix C for an outline of these topics). A shorter training program is preferable because the present study is not geared toward employees completing a mandatory training program. The topics presented include

Table 1

Frequency Table of mTurk Demographics for Pilot Study

Variable	*n*	%
Ethnicity		
African American	3	5.1
Asian	4	6.8
Caucasian	48	81.4
Other	4	6.8
Gender		
Male	22	37.3
Female	36	61.0
Other	1	1.6
Education Level		
High school diploma	5	8.5
Some college	18	30.5
Associate's degree	7	11.9
Bachelor's degree	18	30.5
Master's degree	9	15.3
Doctoral degree	2	3.4
Currently Enrolled in School		
Yes	14	23.7
No	45	76.3
Currently Employed		
Yes	42	71.2
No	17	28.8

$n = 59$

Microsoft Excel basic definitions and commands, basic data analysis, creating graphs, and creating and using macros.

The Microsoft Excel training program was presented in a high learner control format. Participants were provided sequence control in that they were given a navigational menu, present on each page of the training, with an ordered list of topics. Participants could move through each screen in the order laid out in the navigational menu by clicking the "Next" button, they could proceed backwards by clicking the "Previous" button , or they could choose to view selected topics from the navigational menu in any order by clicking on links associated with each topic. Participants had pace control in that they navigated through the training program at the pace of their choosing, moving as slowly or as quickly through the topics as they chose. Finally, participants had content control because they were able to remove content if they chose to skip large or small sections of material; they were not required to view every screen of the training. Participants were also able to add content to the training; the navigation menu contained links to relevant Excel websites related to each topic. Participants did not have advisory control. Learner control features were described in detail to participants using text instructions as well as an instructional video on how to use these features immediately before starting the training program (see Appendix E for text instructions and a transcription of the video).

Measures. All pre-training measures are available in Appendix A, whereas post-training measures are available in Appendix D.

Conscientiousness, openness and extraversion. Saucier's (1994) Mini-Markers scale were used to measure conscientiousness, openness, and extraversion. Each trait is

assessed with eight adjectives, and rated on a five-point Likert scale ranging from 1 (*extremely inaccurate*) to 5 (*extremely accurate*). The scale was chosen in an effort to provide a robust and reliable measure of personality and to reduce participant completion time and cognitive effort prior to training.

According to Saucier (1994), factors derived from Mini-Markers data correlate from .92-.96 to Goldberg's (1993) 100 item Big Five scale. Other researchers report correlations ranging from .56-.85 (Palmer & Loveland, 2003). The Mini-Markers have shown acceptable internal consistency in previous studies, with coefficient alpha estimates ranging from .75-.90 for each scale in those measurement contexts. Additionally, it has shown similar predictive validity to Goldberg's 100-item personality inventory for predicting academic achievement in a sample of 437 undergraduates (Dwight, Cummings, & Glenar, 1998). Palmer and Loveland (2003) provided evidence for construct validity by comparing correlations between the two scales to other criteria such as life satisfaction, emotional intelligence, age, and gender, finding similar criterion-related validities across the Mini Markers and Goldberg's 100 item scale. In the pilot study, coefficient alpha was high for Saucier's measures of conscientiousness ($\alpha = .87$), openness ($\alpha = .82$), and extraversion at ($\alpha = .90$).

Mastery goal orientation. To assess goal orientation, VandeWalle's (1997) scale was used. Each item is rated on a five-point Likert-type scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). Mastery goal orientation (MGO) is measured with five items. An example item measuring mastery goal orientation is "I am willing to select a challenging work assignment that I can work from". The scale showed acceptable internal consistency in a sample of 239 undergraduates, and test-retest reliability in a

separate sample of 53 undergraduates. Coefficient alpha was estimated at .89, and test-retest reliability was estimated at .66 after a three month time lapse (VandeWalle, 1997). Although the test-retest reliability appears low, Payne et al. (2007, p.141) found "no substantial differences" between the VandeWalle (1997) scale and the other two most commonly used goal orientation scales (Button et al., 1996; Elliot & Church, 1997), when assessing measure as a possible moderator. Further, Payne et al. (2007) concluded that VandeWalle's scale produced stronger relationships between goal orientation and task performance, feedback seeking, and self-set goal level. In the pilot study, coefficient alpha for mastery goal orientation was high (α = .88).

Internal locus of control. To assess locus of control, a 15-item measure was taken from Duffy, Downey and Shiflett (1977). This scale was developed as a response to Collin's (1974) adaptation of Rotter's original (1966) scale of locus of control into a 5-point Likert scale. The scale used for this study consists of the three highest loading items for each of the five internal-external scale factors. The five factors are: predictable-unpredictable world, just-unjust world, politically responsive-unresponsive world, easy-difficult world, and friendly-hostile world. Item loadings reported range from .43 to .74, and coefficient alpha for the total scale was reported at .82. Certain subscales correlated moderately to measures of perceived supervisor quality, ambiguity intolerance and Machiavellianism (Duffy, Downey & Shiflett, 1977). In the pilot study, coefficient alpha for internal locus of control was low but approximately at the lower bound of acceptable reliability (α = .68).

Biographical information and content experience. The final questionnaire in the pretest measures asked participants to report demographics such as age, education,

gender, and employment status. Additionally, five questions were asked regarding experience with Excel. The Excel experience measure included questions about familiarity, importance for work or other reasons, and frequency of use for work or other reasons. These questions were taken from previous research regarding learner control and modified for Excel (Freitag & Sullivan, 1995). Coefficient alpha for experience was acceptable ($\alpha = .75$).

Pretraining knowledge. A 24-item multiple choice pretest regarding Microsoft Excel was administered prior to the start of the training program. Pretest scores were used as a control variable in order to examine the training program's effects on learning Microsoft Excel. The questions were used by Sitzmann et al. (2010) and Sitzmann and Ely (2010) to measure knowledge gains in Excel. The test includes items regarding both general and specific information from each of the topics presented in the training program. The same test was used for the post-training knowledge test. The KR-20 estimate of reliability was strong ($\alpha = .79$).

Cognitive ability. General cognitive ability was measured as the number correct out of twelve questions from a publically-available GRE practice test (ETS, 2011). Verbal reasoning was assessed with seven items, and quantitative reasoning was assessed with five items. These questions were chosen in order to balance participant time and cognitive resources spent on this task, with an effective representation of general cognitive ability and test variability. Measures of academic achievement such as the GRE correlate highly with cognitive ability (Ceci, 1996; Neisser et al., 1996). Because GRE practice questions are taken from previously administered GRE tests, these

questions should have adequate validity and reliability to serve as a measure of general cognitive ability.

Cognitive ability has been measured in the learner control literature to date primarily by self-reported GPA (Fisher, Wasserman, & Orvis, 2010; Orvis et al., 2011) and self-reported ACT and SAT scores (Schmidt & Ford, 2003). Participant memory limitations for remembering GPA or SAT scores was a possible concern for self-reported data, as the mean age of mTurk workers was greater than the undergraduate sample by more than ten years. Similarly, the percentage of mTurk workers who have taken a standardized test such as the SAT or GRE was unknown. Based on results from Behrend and colleagues (2011), 68.17% of mTurk workers hold a degree beyond a high school diploma, leaving 31.83% of workers who may have never taken an SAT or GRE test. In the pilot study, participants were asked for their quantitative and verbal SAT scores, as well as their ACT scores. Forty-nine participants did not report an ACT score, 49 did not report a quantitative SAT score, and 48 did not report a verbal SAT score. Ten participants did report an ACT score (M = 28.3, SD = 4.27). After examining the data, it was clear that some respondents who did report SAT scores had taken the older (1600 points possible) version of the SAT and others had taken the new (2400 points possible) version. Seven participants reported an older version quantitative SAT score, ranging from 650 to 800 (M = 694.29, SD = 53.81). Three participants reported a newer quantitative SAT score, and these scores ranged from 1130 to 1440 (M = 1283.33, SD = 155.03). Nine participants reported older verbal SAT scores, ranging from 500 to 800 (M = 645.63, SD = 106.89), and two reported newer verbal SAT scores (M = 1035, SD = 120.21). The amount of missing data indicated that most participants did not report

taking or did not remember their scores on these standardized tests. Thus, GRE practice questions were used in the pilot study to ensure that all participants had an accurate estimate of general cognitive ability. The KR-20 estimate of reliability for cognitive ability from the GRE practice test was high ($\alpha = .79$).

Motivation. Pre-training motivation was measured using an 8 item measure developed by Sitzmann et al. (2010), based on Noe and Schmitt (1986). Items are rated on a 5-point Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). An example item is "I am motivated to learn the skills emphasized in the training program". Noe and Schmitt (1986) reported a coefficient alpha of .81. Motivation was included in the pilot study to investigate differences between pilot groups and differences between mTurk Workers and a parallel undergraduate sample. Coefficient alpha for the motivation measure was high ($\alpha = .88$).

Learner control usage. The usage of learner control features, defined as the amount of control actually exerted throughout the training program, was measured for each type of control.

In order to measure control over sequence, measurement of deviation from the prescribed navigational route, called navigational deviation, was captured (Schrader, Lawless, & Mayall, 2008; Herder & Juvina, 2004). In a program controlled version of a training program, only the "Next" button can be used to progress forward through training. Participants in the current study were given a learner controlled version, and were additionally able to access and use a navigational menu and a "Previous" button. Therefore, a navigational deviation score for each participant was obtained by summing the number of times a participant clicked on the navigational menu or "Previous" button

instead of using the "Next" button alone. Each click on the navigational menu or "Previous" button indicated one usage of sequence control. A higher number indicated greater usage of sequence control, and a lower number indicated lower usage of sequence control. The current slide number appeared at the bottom of each training page (e.g., "Slide 20 of 190") so the participant knew where they currently stood at each step of the training. On the last page of the training, participants were told that they had reached the end of the training ("This completes the course on Microsoft Excel. Please move on to the next page to apply the skills you have learned"). At this point, they could still use the "Previous" button or the navigational menu to go back to previous slides, or they could click an embedded link; "Continue to the Activity". The last link on the navigational menu, visible at all times, read "Finish training and move onto Excel Activity".

The use of pace control is typically quantified by total time on training, but this may not be specific enough to capture control over pacing. An alternative solution to more accurately capture the use of pace control was employed to calculate each person's viewing time for each section of the training. Each participant's viewing time for each topic was calculated in seconds by coding the information derived from tracking records.

Content control was calculated for both the skipping of training content and addition of extra-training content (provided via links to external webpages related to the training content of each subsection). Content removal was measured as the difference between the total number of training pages and number of training pages visited. This difference indicated that the participant did not view all pages of that topic, and has exercised content control by removing content (i.e. higher scores indicate greater removal

of content). Additional content was measured by summing the total number of visits to additional content (external websites found in the navigation menu).

Posttraining knowledge. For the pilot study, learning was assessed by the 24-item multiple choice knowledge test of Microsoft Excel, identical to the pre-training knowledge measure. KR-20 was high for this measure ($\alpha = .91$).

Procedure. Data was collected from three samples of mTurk Workers in order to test the effects of monetary incentives on participant responses. A payment rate of 75 cents for a 30-minute task is considered an appropriate compensation amount for mTurk participants (Barger, Behrend, Sharek & Sinar, 2011). As the training and series of surveys was expected to take a maximum of two hours, $2.00 was the base rate of compensation for the pilot study. The training program was advertised on the Mechanical Turk website, and registered Workers were able to sign up to complete the training program. Pilot participants were all compensated with $2.00 for completing the study regardless of performance. One-third (20) of the participants were assigned to the control group and were not given additional incentives beyond $2.00. A second group of 20 was given a bonus $1.00 incentive for high performance, and a third group of 20 was given a bonus $2.00 incentive. High performance was defined as scoring in the top 40% of pretest to posttest knowledge score increase (i.e., learning increase was measured by subtracting the pre-test score from the post-test score). This difference score thus indicated an increase in learning due to the training program. This was done so that learners who had more pre-training knowledge did not have an advantage to receive the additional compensation. Forty percent was chosen to serve as a difficult but achievable

goal for learning, and to increase the perceived likelihood of receiving the additional incentive.

The entire pilot sample was screened for three qualifications. To participate, Workers needed to be over 18 and native English speakers, with access to Microsoft Excel 2007 or 2010. The first pilot group was given five days to work on the assignment after accepting the HIT, they had to already have at least 50 approved HITs, and their HIT approval rate had to be 99% or greater. Five days completion time was changed to ten hours (200% of the longest completion time for the first group) for groups 2 and 3 because data collection progressed slowly and one person finished the training program five days after they started it. HIT approval rating was also reduced to 95% for the next two groups to combat the slow data collection in the first group. It took 25 days to get 19 participants for the first group, and collection stopped at this point because no one had completed the HIT in four days. Data from twenty participants for both group 2 and group 3 were collected in seven days each. The three groups were collected at separate time points (i.e., group 2 was not advertised on mTurk until collection was complete for group 1) in case Workers could see both HITs at different incentive levels, which could potentially affect their motivation levels. After the first pilot group, an automatic check was added to the website so that no one could repeat the study after completing it once already.

Participants first completed a consent form and pre-training measures, which included all individual difference variables and the pre-training knowledge measure. Participants were provided a text-based overview of how to use the features of learner control so they were aware of the features available and knew how to use them.

Additionally, participants were provided with a video depicting the use of learner control in the training program. Both the text and video emphasized the three types of control provided (sequence, content, and pace) and how to use them. Learner control usage data was collected automatically, based upon actual learner behavior in the program. Once participants completed the training program, they completed the post-training learning outcome measure.

Results

Descriptive statistics and correlations for the individual difference variables can be found in Tables 2 and 3. Sufficient variability and normal distributions were found for each variable, and no outliers were found. Participants reported especially high levels of Mastery Goal Orientation, and answered an average of 5.49 questions correct out of the 12 question cognitive ability (GRE) test.

The data for learner control usage was then examined for outliers. Total time training was examined for outliers, and three were removed from the analysis because the data indicated it was highly likely that that they stepped away from their computer or completed training in an unusual manner. One participant spent one hour on the title page of training, went through the training once, came back five days later, and completed the entire training again. Two other participants were removed because they spent more than two SDs outside the mean training time, one of which spent over thirty minutes on multiple slides. Thus, learner control usage variables were analyzed without those three cases.

Table 2

Descriptive Statistics of Individual Difference Variables for Pilot Study

Variable	*M*	*SD*	Skewness	Kurtosis
1. Excel Experience	2.74	0.87	0.17	-0.38
2. Conscientiousness	3.83	0.71	-0.60	0.29
3. Extraversion	3.28	0.90	-0.31	-0.51
4. Openness	3.90	0.61	-0.17	-0.31
5. Mastery Goal Orientation	4.23	0.63	-0.89	1.17
6. Internal Locus of Control	2.86	0.43	0.13	1.35
7. Cognitive ability	5.49	2.79	-0.16	-0.54

$n = 59$

Table 3

Correlation Matrix of Individual Difference Variables for Pilot Study

Variable	1	2	3	4	5	6	7
1. Excel Experience	--						
2. Conscientiousness	0.05	--					
3. Extraversion	-0.10	0.15	--				
4. Openness	-0.07	0.20	0.25	--			
5. Mastery Goal Orientation	0.31*	0.27*	0.06	0.40**	--		
6. Internal Locus of Control	0.02	0.09	0.26	0.09	0.18	--	
7. Cognitive ability	0.29*	-0.23	-0.20	0.08	0.12	-0.17	--

$n = 59$

In order to also check that participants did not purposely score low on the pretest and score high on the posttest in order to score in the top 40%, outliers were examined for pretest-posttest difference scores, and none were found. The data for pretest-posttest difference scores were normally distributed, and standardized (z-score) values for this variable were all between -2.63 and 2.10.

Examining total time on training was important for the pilot study because of the high level of learner control given; it was possible that learners skipped the entire training program and only completed pre-tests and post-tests. Spending very little time on the training program (or none at all) would be problematic not only for variability in the amount of learner control used, but also in the interpretation of differences between pre- and post-test scores. The original creator of the program evaluated the current version and estimated that it should take approximately 60 minutes to complete the training program. Total time spent training was examined to ensure that pilot participants spent an adequate amount of time on the training program. The average time spent on training was 42.64 minutes (SD = 34.71). The minimum time spent on training was .05 minutes and the maximum time spent training was 142.32 minutes (approximately 2.5 hours). A histogram of the time training can be found in Appendix E, which shows that there was a great deal of variability among time training, with most people spending less than 50 minutes training.

Next, the usage of learner control was examined to determine the extent to which

Table 4

Descriptive Statistics of Training and Learner Control Usage Variables

Variable	*M*	Median	*SD*	Minimum	Maximum	Skew	Kurtosis
1. Total Time Training	42.64	31.11	34.71	0.05	142.32	1.11	0.62
2. Module 1 Time	9.58	5.92	15.99	0.05	109.23	4.98	28.74
3. Module 2 Time	17.63	13.38	15.39	0.00	75.27	1.39	2.49
4. Module 3 Time	9.26	4.59	11.11	0.00	55.35	1.93	4.88
5. Module 4 Time	6.17	5.64	5.48	0.00	23.77	1.14	1.22
6. Sequence	13.05	5.00	22.02	0.00	118.00	3.06	10.58
7. Content Remove	40.05	0.00	60.55	0.00	188.00	1.29	0.25
8. Content Add	0.36	0.00	0.67	0.00	3.00	2.04	4.10

n = 56

Table 5

Correlation Matrix of Training and Learner Control Usage Variables

Variable	1	2	3	4	5	6	7
1. Total Time Training	--						
2. Module 1 Time	.67**	--					
3. Module 2 Time	.79**	.19	--				
4. Module 3 Time	.77**	.33*	.52**	--			
5. Module 4 Time	.60**	.09	.58**	.44*	--		
6. Sequence	.44**	.06	.49**	.44*	.38**	--	
7. Content Remove	-.38**	-.03	-.32*	-.45**	-.52**	-.22	--
8. Content Add	-.07	.03	-.07	-.14	-.07	.24	.28*

n = 56

participants used learner control features; sufficient variability in usage of these features was needed for analyses in the main study. Descriptive statistics for each type of learner control (pace, sequence, and content) can be found in Table 4. Average time per module varied, ranging from 6.17 minutes to 17.63 minutes. Most participants (89.3%) used sequence control at least once, and participants averaged approximately 13 uses of control over sequence. The majority of participants (64.3%) did not choose to remove content, i.e., they viewed all of the slides in the training program. Approximately 40 slides were removed from training, on average. Lastly, few participants (26.7%) chose to add content by visiting outside websites with additional information. Those who did add content visited between one and three additional websites.

Because of the small sample size, correlations between learner control usage variables were examined (see Table 5). This was done to provide preliminary evidence regarding whether learner control usage can be entered into the full study hypothesized models as one unidimensional construct. Time training correlated significantly and positively with usage of sequence control, and negatively with content remove. Content add and content remove correlated positively and significantly at .28.

Independent-samples t-tests were used to compare mean differences in certain variables between the undergraduate and mTurk samples, and can be found in Table 6. Because multiple t-tests were utilized, a Bonferroni correction was used to control for Type I familywise error, and alpha was set at 0.008333. The undergraduate sample was an average of 23.65 years old, which was significantly lower by 10.21 years from the mTurk sample. mTurk Workers reported significantly higher levels of pre-training motivation than undergraduates and scored significantly higher on the pre-training

Table 6

t-test Results Comparing Undergraduate Students and mTurk Workers

Variable	*t*	df	*p*	Mean Difference	CI LL	CI UL
Pre-training Motivation	4.65	97	< 0.001	0.57	0.33	0.81
Pre-training Computer Knowledge	4.70	97	< 0.001	3.84	2.22	5.46
Age	5.29	97	< 0.001	10.21	6.38	14.05
Declarative Knowledge Pretest	2.85	97	0.005	2.26	0.69	3.83
Declarative Knowledge Posttest	2.89	97	0.005	3.30	1.03	5.57
Total Time Training	1.35	92	0.179	9.42	-4.39	23.23

Note. mTurk $n = 59$ and undergraduate $n = 40$ for all tests except for Total Time Training DV, in which case n = 56 and 38, respectively. CI = confidence interval; LL = lower limit; UL = upper limit.

computer knowledge measure. As discussed in the previous paragraphs, three outliers were removed for total time training due to unusually high training times. No outliers were removed from the undergraduate sample because time per training slide was not recorded for that data. Undergraduates spent an average of 33.22 minutes on the training program, and mTurk workers spent an average of 42.64 minutes on training. This difference of 9.42 minutes was not statistically significant, though without the removal of outliers, the difference between mean training times would have been significant. Undergraduates scored an average of 10.23 questions correctly (out of 24) on the pretraining Excel questions. The mTurk sample answered an average of 7.97 questions correctly, and this difference of 2.26 was significant. Undergraduates scored an average of 12.83 questions correctly on the posttest, and mTurk Workers scored an average of 16.12 questions correctly. The 3.30 point difference in posttest scores differed significantly between the undergraduate and mTurk samples (see Table 6).

A repeated-measures ANOVA was used to examine the differences between declarative knowledge gain from the Excel training program. Assumptions for ANOVA were checked prior to analysis; no extreme outliers were found, the data was normally distributed, and Levene's test of homogeneity of variance for both the pretest and posttest indicated that the assumption of homogeneity of variance was met, $F(1, 97) = 3.26, p = .074$ and $F(1, 97) = 2.24, p = .138$. Results for the ANOVA can be found in Table 7. The ANOVA results indicated that mTurk Workers learned significantly more from the training program than undergraduate students; the interaction between sample group and knowledge change was significant (see Table 7).

Table 7

Repeated Measures ANOVA for Knowledge Change Between Undergraduates and mTurk Workers

	Pretest		Posttest		SS	*df*	*MS*	*F*	*p*	partial η^2
	M	*SD*	*M*	*SD*						
Time	8.99	3.98	14.76	0.95	1324.89	1	1324.89	97.85	< .001	0.51
Interaction					344.94	1	344.94	25.48	< .001	0.21
mTurk	7.97	4.39	16.12	5.85						
Undergrad	10.23	2.93	12.83	5.07						
Error					1286.29	95	13.54			

$n = 97$

Table 8

Analysis of Variance Results for Comparisons Between Pilot Groups

Source	SS	*df*	*MS*	*F*	*p*	partial η^2
Time Training	5198.34	2	2599.17	0.88	0.419	0.03
Error	16476.90	56	2942.28			
Motivation	0.40	2	0.20	0.67	0.515	0.02
Error	16.80	56	0.30			

n = 56 for Time Training, *n* = 59 for Motivation.

Table 9

Repeated Measures ANOVA for Knowledge Change Between Pilot Groups

	Pretest		Posttest		SS	*df*	*MS*	*F*	*p*	partial η^2
	M	*SD*	*M*	*SD*						
Time	8.11	4.40	16.12	5.85	1846.05	1	1846.05	114.43	< .001	0.68
Interaction					40.32	2	20.16	1.25	0.295	0.04
Pilot 1	7.63	4.00	14.53	6.86						
Pilot 2	7.90	4.69	15.45	6.16						
Pilot 3	8.83	4.62	18.56	3.29						
Error					871.18	54	16.13			

n = 57

Lastly, ANOVAs were used to test the effects of top performance incentives on motivation, time spent on training, and learning gain in order to decide upon the incentive structure for the full study. Results for motivation indicate no significant differences between pilot groups (see Table 8). The mean motivation scores on a 5-point scale for pilot groups 1, 2, and 3 were 4.31, 4.51, and 4.42, respectively. Mean time spent training also did not differ significantly by pilot group (see Table 8). Mean times for groups 1, 2, and 3 were 68.95 minutes, 50.20 minutes, and 47.75 minutes, respectively. Lastly, a repeated-measures ANOVA indicated that learning did not differ by pilot group (see Table 9).

Discussion

The pilot study data collection and analysis were completed in order to examine data from several individual difference variables, training variables, and learner control usage variables, to compare mTurk Workers to an undergraduate sample, and compare the effects of different incentive schemes. The results of the pilot study informed several decisions made regarding the incentive structure, qualifications, and participant limitations for full data collection.

First, descriptive statistics from demographic and individual difference variables were satisfactory for the purposes of this project. The average age of 33.86 years was desirable for generalizing to an employee population, especially when compared to the average undergraduate age of 23.65 years. Most participants (91.5%) had completed at least some college, which is close to what one might expect for an employee whose job requires knowledge of Microsoft Excel. Most mTurk participants (81.4%) were Caucasian, indicating fairly low variability in ethnicity, though this breakdown is

typically found in a sample of undergraduates as well. A very large percentage (71.2%) of Workers were currently employed. Although this population is clearly not drawn from a single organization, more Workers are employed than is typical in undergraduate samples. Individual difference variables (experience, personality, goal orientation, locus, and cognitive ability) were all normally distributed and showed sufficient variability and high internal consistency. One minor exception was the internal consistency of the Internal Locus scale, with an alpha of .68. This estimate was lower than .82, which was reported by the creators of the measure (Duffy, Downey, and Shiflet, 1977). However, this estimate in a sample of 59 participants is not far from the commonly accepted minimum of .70. Overall, results indicate that these measures should be reliable measures for use with the mTurk population.

Examination of descriptive statistics of training and learner control usage variables revealed unexpected results. Time training was lower than the expected one hour (42.64 minutes, not including 3 outliers outside of +2 SD from the mean training time). Time training was not significantly different than the undergraduate sample, which may indicate that the completion time for this training program may simply take most people less time than the designer intended. The training program contains 190 slides, though the amount of detailed information on each slide is fairly small; most slides contain a short title, a short (5-6 item) bulleted list, or two sentences and an Excel screenshot. In general, fewer Workers utilized learner control than one might expect. Distributions for each type of control were quite kurtotic and positively skewed. Regardless, no study has been published which measures the amount of learner control utilized, so this is a valuable finding in itself. These distributions may pose problems for

analysis however, so for the full study, this will be addressed by dichotomizing and transforming these variables, if the distributions remain severely non-normal.

Correlations between the types of learner control usage variables were surprising; few were statistically significant and a few were unexpectedly negative. Based on these low and sometimes negative correlations between types of learner control usage, learner control usage behavior does not appear to be a unidimensional construct. These correlations indicate that usage of the different types of learner control should be examined separately for the full study. It is possible that the low sample size and low variability in adding content contributed to these results. It is also possible that the measurement of these variables actually indicated quite different behaviors during training. Based on this evidence, it appears that these behaviors should be modeled as individual, unique behavioral dimensions. As a result of the pilot, the original model including one learner control usage variable was tested in the full study, but an additional model with distinct behavioral constructs was also tested. The use of content control for adding content was examined during the full study because of the low variance in the pilot study.

Compared to undergraduates, it appears that mTurk Workers are a desirable sample for this study. Demographics such as age, education, and employment status are more similar to employee samples than undergraduate samples typically are. Beyond that, Workers reported being significantly more motivated pretraining, and learned more than undergraduate students taking the same training program. Interestingly, Workers had significantly lower pretraining Excel knowledge by 2.26 points, but surpassed the post-training scores of undergraduates by 3.30 points. mTurk Workers scored

significantly higher on the pre-training computer knowledge test than undergraduates, and this may or may not be more like the level of actual employees, depending on the technology requirements of a specific job. In general, mTurk Workers seem to be preferable over an undergraduate sample for this study.

Lastly, ANOVA analyses revealed no significant differences between the three pilot groups in regards to motivation, time training, and learning outcomes. There were small differences in the qualifications and limitations between the first group and the following two groups aside from incentives (less time allowed to complete the HIT and a lower minimum previous HIT acceptance rate), which does cloud the effects of the differing incentives. However, these qualifications had to be changed for practical purposes (data collection time) and data quality (large 5-day lapses in finishing the study). Because no significant differences were found between the three pilot groups on motivation, time training, and learning outcomes, no additional incentives beyond the baseline payment were used for the full study.

Summary of Implications for Main Study

The purpose of the main study was to test the hypothesized models of learner control. Participants completed the same training program, individual difference measures, and learning measures as the participants in the pilot study. The usage of learner control during the training program was then examined as a partial mediator in the relationship between those hypothesized individual differences and learning outcomes. The pilot study was conducted to examine variability in learning outcomes, differences between mTurk and undergraduates, and degree of monetary incentives influencing participation. Results indicated that pretest and posttest Excel knowledge had adequate

variability, that there were few but desirable differences between mTurk Workers and undergraduate students, and that monetary incentives did not significantly impact participation. Therefore, Amazon Mechanical Turk was used to recruit participants for the main study, and one flat-rate incentive was given to all participants.

CHAPTER III

METHOD

Participants

In order to determine the number of participants necessary to test the proposed models, a power analysis was conducted. Equations from Kim (2005) were used to conduct a power analysis for RMSEA, CFI, McDonald's Fit Index (MFI), and Steiger's γ. Sample sizes required depends on several factors, including the distributions and reliability of variables, relationships among the variables, simplicity of the model, missing data, and which fit index is examined. Kim (2005) recommends conducting a power analysis for several fit indices. Thus, required sample sizes at 80% power were calculated for four fit indices, and the mean sample from these four estimates was used as the power analysis estimate for required sample size. SPSS syntax was taken from a website created by Timo Gnabs (timo.gnambs.at/en/scripts/powerforsem). In accordance with recommendations from Hu and Bentler (1999), fit values of .90 for MFI, .05 for RMSEA, and .95 for CFI and Steiger's γ were used. To test the model as a path model, the required samples were 316, 88, 247, and 120 for RMSEA, Steiger's γ, CFI, and MFI, respectively. The average of these indicates that 193 participants were needed for 80% power to find the hypothesized effects.

Participants were recruited from Amazon Mechanical Turk, approximately two months after data collection stopped for the pilot study. A total of 231 mTurk Workers submitted a HIT for the study. Of those 231 submissions, 23 were rejected within mTurk for bad responses (i.e., long strings of the same responses on multiple survey pages), inordinately low time spent on surveys (e.g., completing the 12-item cognitive ability

measure in 30 seconds) and/or for incomplete submissions (i.e., not all surveys were completed). Those 23 cases were removed for the purposes of data analysis, as those responses could severely distort the results, bringing the total sample size to 208.

The data were inspected for improbable values, and several were found and removed. The following datapoints were removed and changed to missing values: two participants reported current GPAs above 4.00, nine participants reported not being currently enrolled in school but reported their current GPAs as 0, eight participants reported they did not work but listed 0 for working hours, two participants reported ACT scores above the maximum score of 36, and one person reported working for mTurk for 98 hours per week.

Frequencies of demographic variables (see Table 10) revealed that full study participants had similar attributes to those participants in the pilot study. The majority (75.48%) were Caucasian, most were female (63.94%), and many participants had attended some college (32.21%) or completed a Bachelor's degree (37.02%). The majority of participants (69.23%) were currently employed and of those who were currently employed, 65.27% considered their current job to be their career. Lastly, only 62 participants (29.81%) had previously taken a course in Excel before completing this study.

Materials

The same Microsoft Excel training program was used for the full study, and included the same training content and learner control features. Two changes were made to the training program between the pilot study and the full study. Both changes had

Table 10

Frequency Table of mTurk Demographics

Variable	n	%
Ethnicity		
African American	22	10.58
American Indian/Pacific Islander	3	1.44
Asian	14	6.73
Caucasian	157	75.48
Hispanic	7	3.37
Other	5	2.40
Gender		
Male	75	36.06
Female	133	63.94
Education Level		
Some high school	1	0.48
High school diploma	10	4.81
Some college	67	32.21
Associate's degree	17	8.17
Bachelor's degree	77	37.02
Master's degree	28	13.46
Doctoral degree	8	3.85
Currently Enrolled in School		
Yes	44	21.15
No	164	78.85
Currently Employed		
Yes	144	69.23
No	64	30.77
If Employed, Career Job		
Yes	94	65.27
No	49	34.03
Previous Excel Course Taken		
Yes	62	29.81
No	146	70.19

$n = 208$

been indicated by participants in open-ended feedback at the end of the pilot study. First, the training directions text was edited to be more clear (a few participants complained they could not access the training during the posttest knowledge measures, so text was added that indicated that they could no longer view the training once they moved on to the post training measures). Second, one of the training slides appeared out of order in the pilot study, which was corrected for this study. All other aspects of the training program were exactly the same between the pilot and full studies.

Measures

Identical measures were used for the full study. A few minor changes were made to the measures for the full study, based on feedback from participants and further editing for clarity. These changes included two questions on the Excel pre and posttest, and the upload feature for the Excel activity/skill test. One question on the pre and posttest referred to two datasets, but the dataset images did not appear correctly. This issue was fixed, as was another image included on a second question, whose arrows did not appear correctly at certain parts of the image. After the training program, participants were directed to a post-training skill activity in both the pilot and full studies. The activity was completed and submitted by uploading to the website (see Appendix D for the activity instructions). One critical issue was discovered during data collection for the pilot study; the website originally did not accept Macro-enabled Excel workbooks for the post training Excel activity, disallowing some participants in the pilot study from submitting their work. This was fixed for the main study.

Learner control usage. The usage of learner control features were again measured for each type of control. One difference between the pilot study and the full

study was that tracking data was coded by hand for the pilot study. For the full study, a website was created to automatically sum the usages of learner control, the time spent in each section of the training, and the total time.

In order to analyze learner control usage in the hypothesized model, each participant's score for sequence, pace, and content was converted into a z-score. This process to standardize sequence control, removing content and adding content was straightforward; z-scores of those counts were taken for each participant. Quantifying pace control took several steps. Topic viewing time for each of the four modules was subtracted from the average viewing time for all participants for that topic. The absolute values of those difference scores were summed to produce a single score to quantify the use of pace control for the training program. It is important to note that larger scores indicate greater usage of pace control during the training program, not necessarily more time spent on the training program; only the exertion of control was measured. The sum of each participant's absolute deviation scores indicated overall use of pace control for the training program.

Learning outcomes. For the full study, learning was assessed by the 24-item multiple choice knowledge test of Microsoft Excel, identical to the pre-training knowledge measure, as well as a Microsoft Excel skill activity. This activity included the opportunity to demonstrate knowledge gains in the skills taught during the training program. Participants complete this activity immediately following the training program, and the submitted activities were scored by a key. This activity can be found in Appendix D. A possible 30 points could be earned. Up to five points were awarded for successfully completing the following tasks; summing numbers using a range by day,

creating a name based on time period, summing time periods using the name, creating a chart based on day, creating a chart based on time, and creating a macro to remove the color coding from the data. Coefficient alpha for the skill measure was high ($\alpha = .78$).

Procedure

This training program was advertised again on the Mechanical Turk website, and registered Workers were able to sign up to complete the training program, just as participants in the pilot study. The rate of compensation was $2.50 for the full study, and no bonuses were advertised or given to participants. The automatic check remained in place so that Workers who had completed the pilot study could not complete the full study. Screening criteria included being over the age of 18, being a native English speaker, and having access to Microsoft Excel 2007 or 2010. The longest non-outlier training time from the pilot was added to the longest non-outlier survey completion time for the pilot, and this did not exceed seven hours, so the HIT completion time was changed to a maximum of seven hours. HIT approval rating remained at 95%, as did a minimum of 50 previously accepted HITs.

As in the pilot study, participants first completed a consent form and pre-training measures, including individual difference variables, demographics, and the pre-training knowledge measure. Participants were provided with both a text overview and a video explaining the features of learner control available in the training program. Learner control usage data was collected using tracking cookies and control over each type was automatically summed. After the training program, participants completed the Excel skill activity and multiple choice knowledge measure.

CHAPTER IV

RESULTS

Prior to hypothesis testing, the dataset was cleaned and screened for missing data, outliers, and non-normality for all variables. Missing data was minimal for variables in the path model. Mplus uses Expectation-Maximization (EM) algorithm to automatically impute missing data. According to the covariance coverage matrix, between 83.2% and 100% of the data was present for each variable. The lowest percentage of present data was for the skill measure at 83.2%. All other variables contained data for between 96.6% and 100% of the data points. The low coverage for the skill measure was due to the nature of that variable; participants had to upload an Excel document in order for it to be scored. Nineteen participants were unsuccessful in uploading a file to the website, and an additional sixteen people uploaded blank or unchanged Excel documents. Because it was unlikely that the uploaded blank files reflected a complete lack of Microsoft Excel skill, those files were not scored or included in the analysis.

All individual difference, knowledge, and learner control variables were then inspected for normality. After inspecting histograms of the data and examining skewness and kurtosis estimates, the individual difference and knowledge measures appeared normally distributed, except for the Excel skill test. The histogram of the skill data was negatively skewed (see Appendix E). Because model fit in SEM may be degraded due to univariate non-normality, especially due to extreme skewness (West, Finch, & Curran, 1995), the skill test data was transformed using Box-Cox transformations, using syntax taken from Osborne (2010). Box-Cox transformations are a family of power transformations, which include traditional transformations such as logarithmic, square

root, and inverse transformations. These transformations were performed in order to best normalize the distribution without needing to randomly attempt multiple types of transformations. According to Osborne (2010), Box-Cox transformations are considered a "potential best practice where normalizing data or equalizing variance is desired" (p. 1). For the Excel skill test, the variable was anchored at 1.0, and the Box-Cox transformation coefficient, lambda, was estimated at .1 increments between .9 and 3.0. The lambda value of 1.1 was maximally effective in transforming the distribution (skew = -.518, kurtosis =-.874). Thus, the transformed skill variable was used for SEM analyses.

This study is the first to measure usage of pace, content, and sequence control. Thus, it was decided that outliers be examined individually. In order to ensure the data collected was meaningful in measuring learner control usage, it was decided that cases with extreme outliers more than three standard deviations from the mean may be deleted on a case-by-case basis, pending an examination of other variables, such as total time on training and missing data on other measures.

All data were examined for outliers, and none were found for the individual difference variables or learning outcome measures, but several were found for the learner control usage variables. Four cases were flagged as outliers in the boxplot for sequence control usage data, and each had extremely high values for uses of sequence control (between 79 and 169 uses, z-scores for sequence ranged from 3.26 to 7.88). These participants scrolled through many slides in short periods of time, using the "Previous" button. The original definition of sequence control (using any button except the "Next" button), counts participants who use the "Previous" button many times in a row, spending very little time viewing the slides between their start point and intended end point.

However, this does not accurately capture the intended construct (e.g. clicking back twenty times to move from Slide 40 to Slide 20 should not represent 20 decisions to use sequence control). Two extreme outliers were found for total time in training. Two participants spent over four hours and six hours training, respectively (z-scores for time = 8.05 and 5.26). One participant was flagged as an outlier for the usage of multiple control features. The participant used sequence control 62 times but only viewed 45 slides of the 190 slide training, with a total time of 2 minutes spent on the training program website. All data for learner control usage for these seven participants were removed.

Psychometric Properties of Measured Variables

After data cleaning, reliabilities, descriptive statistics, and correlations were calculated for each study variable, which can be found in Tables 11 and 12. Alpha was acceptable for all individual difference variables and knowledge measures (between 0.75 and 0.86) with the exception of internal locus of control, which was slightly below acceptable ($\alpha = 0.65$). Excel experience was positively correlated with hours worked per week, MGO, and cognitive ability. Surprisingly, cognitive ability was negatively correlated with both conscientiousness and extraversion.

Learner control usage variables were further inspected for interrelationships, sufficient variability, and normality. Sequence control was negatively correlated with content remove, positively related to total time training, and had no relationship to content add. Content remove was positively correlated with content add, and negatively related to time training. There was no relationship between content add and total time

Table 11

Descriptive Statistics of Study Variables

Variable	*n*	*M*	*SD*
1. Age	207	32.67	10.46
2. GPA at Highest Education Level	160	3.42	0.45
3. Current GPA	36	3.45	0.53
4. Hours Worked per Week	131	37.83	9.92
5. Microsoft Excel Experience	208	2.74	1.01
6. Openness	208	3.89	0.61
7. Conscientiousness	208	3.80	0.68
8. Extraversion	208	2.93	0.79
9. Mastery Goal Orientation	208	4.22	0.62
10. Internal Locus of Control	208	2.74	0.43
11. Cognitive Ability	208	5.25	3.07
12. Pretraining Excel Knowledge	207	8.99	4.28
13. Post-training Excel Knowledge	199	15.91	4.45
14. Post-training Excel Skill	173	22.98	5.82
15. Sequence Control	201	13.05	13.01
16. Content Remove	201	48.03	67.91
17. Content Add	201	0.37	0.77
18. Total Time Training (minutes)	201	37.25	31.35

Table 12

Correlation Matrix Between Study Variables

Variable	1	2	3	4	5	6	7	8	9
1. Age	--								
2. GPA at Highest Education Level	-.06	--							
3. Current GPA	.22	.64**	--						
4. Hours Worked per Week	.01	.16	.47*	--					
5. Microsoft Excel Experience	.13	-.02	.03	.20*	**.79**				
6. Openness	.10	.14	.13	-.05	.01	**.75**			
7. Conscientiousness	.02	-.02	-.07	.13	.05	.16*	**.84**		
8. Extraversion	.11	-.04	.07	.00	.05	.13	.21**	**.83**	
9. Mastery Goal Orientation	.09	-.06	-.04	.00	.17*	.37**	.31**	.28**	**.86**
10. Internal Locus of Control	-.17*	.01	-.07	.05	.05	-.07	.10	.33**	.10
11. Cognitive Ability	.11	.02	.29	-.06	.22**	.23**	-.20**	-.16*	.12
12. Pretraining Excel Knowledge	-.03	-.01	-.14	.03	.48**	.09	-.06	.04	.10
13. Post-training Excel Knowledge	.07	-.03	.01	-.01	.21**	.10	-.05	-.16*	.05
14. Post-training Excel Skill	.05	-.04	.15	.03	.21**	-.05	-.13	-.17*	.07
15. Sequence Control	.16*	.06	-.06	-.06	.03	.09	.07	-.04	.12
16. Content Remove	-.15*	-.01	-.10	.02	-.04	-.24**	-.13	.10	-.10
17. Content Add	-.14*	.07	-.02	-.01	.03	.06	.06	-.03	-.01
18. Total Time Training (minutes)	.28**	.05	-.10	-.04	-.01	.18*	.21**	-.04	.18*

(Table 12 continued)

Variable	10	11	12	13	14	15	16	17
10. Internal Locus of Control	**.65**							
11. Cognitive Ability	-.13	**.76**						
12. Pretraining Excel Knowledge	-.04	.28**	**.78**					
13. Post-training Excel Knowledge	-.06	.46**	.50**	**.79**				
14. Post-training Excel Skill	.05	.42**	.20**	.48**	**.78**			
15. Sequence Control	.05	.19**	-.01	.25**	.25**	--		
16. Content Remove	.11	-.24**	-.11	-.38**	-.09	-.34**	--	
17. Content Add	.08	.09	-.02	-.02	-.02	.05	.20**	--
18. Total Time Training (minutes)	-.06	.20**	-.09	.30**	.19*	.54**	-.59**	.04

training. Low variability was found for the content add variable (see Appendix E for histogram of the raw data). On average, participants added .37 websites to their training (SD = 0.77). Only 51 out of the final set of 201 participants visited any extra-training websites, and only sixteen of those who did visit those websites viewed more than one. In order to address the low variability, content add was added to content remove. However, this new content total variable did not correlate with any other learner control usage variables. Additionally, the correlation of only .20 did not indicate that the same people were both adding and removing content, so the content total control variable was not used. It was determined that content add would be attempted as a measured indicator as part of unidimensional learner control factor, but that it may need to be dropped from analyses due to low variability. The other relationships (especially the negative relationship between sequence and content remove) indicated that a unidimensional learner control usage variable would need to be investigated but may not provide adequate fit.

The following decisions were made regarding learner control variables for analysis in SEM. Because the data for sequence control and time training for each module were severely non-normal (see histograms in Appendix E), a series of Box-Cox transformations were used to determine the ideal transformation for those variables. The same procedure as the Skill test transformation was followed, but lambdas of -2.1 to 1 were used because of the positive skew of these variables. Lambdas of .1 for sequence and .3 and .4 for the four training module times best addressed the non-normality, so those transformed variables were used for analyses. The content remove variable was also problematic; about half of participants did not remove content (i.e., they viewed all

training slides). The distribution was severely skewed and kurtotic. Content remove was dichotomized, but this was unhelpful in attempts to measure total learner control.

Fitting the Measurement Model

Numerous iterations of a possible latent learner control measurement model were attempted. A one-factor unidimensional model, with sequence, content add, content remove, and time training indicators was modeled, but the analyses would not converge. Every possible combination of raw, transformed, dichotomized, and polytomized variables were attempted. Only one model of only absolute deviation time scores loaded onto one factor successfully, but neither of the other two learner control usage variables related in any meaningful way. Because of estimation problems in Mplus for a dichotomous content remove variable, it was polytomized into 0 usage, and 4 quartiles of amount of content removed (i.e., 5 total categories). This allowed content remove to remain in the model without creating errors. Thus, three measured and correlated learner control usage variables were used as mediators in each of the hypothesized model tests; polytomized content remove, sum of absolute deviation time per section (transformed), and transformed sequence control.

Measurement models were attempted for each of the individual difference variables. See Tables 13 and 14 for model fit and factor loadings for each scale. MGO was the only scale with acceptable fit and factor loadings for each item, so this scale was left as-is. Excel experience (five items) showed poor fit, and one item in

Table 13

Model Fit Statistics for Scale Measurement Models, All Items Loaded Onto One Factor

Model	χ^2	df	p	CFI	AIC	RMSEA	SRMR
1. Experience	41.955	5	<0.000	0.790	1588.313	0.267	0.078
2. Openness	178.307	20	<0.000	0.656	4474.064	0.195	0.109
3. Conscientiousness	174.173	20	<0.000	0.771	4166.439	0.193	0.089
4. Extraversion	116.522	20	<0.000	0.823	4826.905	0.152	0.076
5. Mastery Goal Orientation	7.722	5	0.172	0.994	1961.966	0.051	0.019
6. Internal Locus of Control	580.282	90	<0.000	0.303	8974.636	0.162	0.148
7. Cognitive Ability	578.870	30	<0.000	0.904	----	0.084	1.055*

*WRMR (Weighted Root Mean Square Residual) is reported for dichotomous items.

Table 14

Item Loadings for Scale Measurement Models, All Items Loaded Onto One Factor

Scale/Item	β	S.E.	*t*	*p*
Experience				
Familiarity with Microsoft Excel	0.657	0.068	9.650	<0.000
Importance of Microsoft Excel for Work or School	0.781	0.055	14.322	<0.000
Important of Microsoft Excel for Reasons Other than Work or School	0.379	0.100	3.804	<0.000
Frequency of Microsoft Excel Use for Work or School	0.831	0.051	16.247	<0.000
Frequency of Microsoft Excel Use for Other Reasons	0.559	0.080	6.970	<0.000
Openness				
Complex	0.270	0.072	3.731	<0.000
Creative	0.786	0.038	20.711	<0.000
Deep	0.381	0.068	5.596	<0.000
Imaginative	0.768	0.039	19.565	<0.000
Intellectual	0.286	0.072	3.992	<0.000

(Table 14 continued)

Scale/Item	β	S.E.	*t*	*p*
Philosophical	0.379	0.067	5.650	<0.000
Uncreative*	0.759	0.041	18.369	<0.000
Unintellectual*	0.312	0.073	4.274	<0.000
Conscientiousness				
Careless*	0.619	0.049	12.755	<0.000
Disorganized*	0.804	0.033	24.142	<0.000
Efficient	0.530	0.057	9.223	<0.000
Inefficient*	0.689	0.044	15.639	<0.000
Organized	0.764	0.037	20.843	<0.000
Practical	0.378	0.066	5.739	<0.000
Sloppy*	0.787	0.034	23.494	<0.000
Systematic	0.349	0.067	5.219	<0.000

(Table 14 continued)

Scale/Item	β	S.E.	*t*	*p*
Extraversion				
Bashful*	0.610	0.053	11.567	<0.000
Bold	0.563	0.055	10.165	<0.000
Energetic	0.378	0.069	5.489	<0.000
Extraverted	0.696	0.046	15.117	<0.000
Quiet*	0.742	0.040	18.433	<0.000
Shy*	0.764	0.041	18.659	<0.000
Talkative	0.627	0.051	12.329	<0.000
Withdrawn*	0.482	0.060	8.070	<0.000
Mastery Goal Orientation				
Select Challenging Assignments	0.775	0.034	22.688	<0.000
Look for Opportunities to Develop New Skills and Knowledge	0.657	0.045	14.661	<0.000

(Table 14 continued)

Scale/Item	β	S.E.	*t*	*p*
Enjoy Challenging and Difficult Tasks	0.856	0.028	31.023	<0.000
Developing Work Ability is Important Enough to Take Risks	0.745	0.037	19.910	<0.000
Prefer Work Situations Requiring High Ability and Talent.	0.722	0.039	18.485	<0.000
Internal Locus of Control				
No Such Thing as "Luck"	0.860	0.044	19.641	<0.000
Impossible That Chance or Luck Play an Important Role	0.776	0.043	18.208	<0.000
Unhappy Things are Due to Bad Luck*	0.444	0.065	6.833	<0.000
Lonely People Do Not Try to be Friendly	0.341	0.071	4.768	<0.000
Misfortunes Result from Lack of Ability, Ignorance, or Laziness	0.331	0.073	4.503	<0.000
People Who are Not Liked Do Not Understand How to Get Along	0.175	0.078	2.241	0.025
People Can Control World Events	0.053	0.077	0.686	0.493
Average Citizens Can Influence Government Decisions	0.153	0.075	2.030	0.042

(Table 14 continued)

Scale/Item	β	S.E.	*t*	*p*
Difficult to Have Control over Politicians in Office*	-0.114	0.077	-1.486	0.137
The Boss was Lucky to be in the Right Place First*	0.149	0.077	1.923	0.054
Have Little Influence over What Happens to Me	0.002	0.078	0.021	0.983
People's Worth Often Passes Unrecognized*	0.005	0.079	0.057	0.954
Wars Exist because of Disinterest in Politics	0.230	0.076	3.009	0.003
War will Exist, Regardless of People trying to Prevent them*	-0.068	0.076	-0.891	0.373
No Matter how Hard you Try, Some People Just Don't Like You*	0.132	0.076	1.739	0.082
Cognitive Ability				
Verbal				
Q1	0.707	0.066	10.712	<0.000
Q2	0.520	0.079	6.610	<0.000
Q3	0.604	0.074	8.105	<0.000

(Table 14 continued)

Scale/Item	β	S.E.	*t*	*p*
Q4	0.772	0.058	13.391	<0.000
Q5	0.751	0.061	12.414	<0.000
Q6	0.775	0.058	13.352	<0.000
Q7	0.888	0.050	17.785	<0.000
Quantitative - choose which quantity is greater				
Q1	0.165	0.095	1.739	0.082
Q2	0.590	0.073	8.100	<0.000
Quantitative - choose the correct answer				
Q1	0.404	0.107	3.771	<0.000
Q2	0.554	0.077	7.210	<0.000
Q3	0.274	0.092	2.985	0.003

Note. Full text of items is available in Appendix A. *Item was reverse-coded

particular had low correlations with other items and a low factor loading (.379). The item was created for the study ("How important is using your current knowledge of Microsoft Excel for reasons other than work or school?"). This item was dropped, and adequate model fit and factor loadings were found for the new 4-item scale. Alternative models with 2 factors (all items and negative item factors) were tested for each scale containing negative items (i.e., the three personality variables and internal locus). This approach did not improve measurement model fit to an acceptable level. Therefore, a conservative parceling strategy was employed for each scale. Items were randomly chosen to form parcels. Eight-item personality scales (openness, conscientiousness, and extraversion) were converted into four parcels of two random items, 12-item cognitive ability was converted into four parcels of 3 random items, and 15-item internal locus was converted into five parcels of three items. Each of these parceled scales showed acceptable model fit and factor loadings and were used to test the hypothesized models. Because the aims of this study were more aligned with testing individual differences' relationships to other variables, and not on the scales themselves, this was a desirable strategy to remove error from the hypothesized models, stemming from the measurement models. Model fit and factor loadings for the final models can be found in Tables 15 and 16.

Hypothesis Testing

Hypothesized models were tested using Mplus 5.2 with bias corrected bootstrapping and 1,000 replications, as recommended by Preacher and Hayes (2008). Overall model fit was examined in order to infer how well the variances and covariances of the model were predicted by the theoretical relationships. Multiple global fit indices;

Table 15

Model Fit Statistics for Scale Measurement Models, Final Scales

Model	χ^2	df	p	CFI	AIC	RMSEA	SRMR
1. Experience	6.231	2	0.044	0.984	2491.116	0.101	0.026
2. Openness	7.879	2	0.020	0.978	1692.554	0.119	0.028
3. Conscientiousness	2.486	1	0.115	0.996	1666.601	0.085	0.016
4. Extraversion	7.333	2	0.026	0.982	2054.595	0.113	0.022
5. Mastery Goal Orientation	7.722	5	0.172	0.994	1961.966	0.051	0.019
6. Internal Locus of Control	1.654	3	0.647	1.000	1997.189	0.000	0.017
7. Cognitive Ability	4.270	2	0.118	0.988	2210.984	0.074	0.022

Table 16

Item Loadings for Scale Measurement Models, Final Scales

Scale	β	S.E.	*t*	*p*
Experience				
Familiarity with Microsoft Excel	0.679	0.048	14.261	<0.000
Importance of Microsoft Excel for Work or School	0.731	0.042	17.585	<0.000
Important of Microsoft Excel for Reasons Other than Work or School	0.876	0.036	24.533	<0.000
Frequency of Microsoft Excel Use for Work or School	0.529	0.057	9.311	<0.000
Openness				
Parcel 1	0.743	0.044	16.740	<0.000
Parcel 2	0.548	0.056	9.768	<0.000
Parcel 3	0.692	0.046	15.163	<0.000
Parcel 4	0.846	0.039	21.965	<0.000

(Table 16 continued)

Scale	β	S.E.	*t*	*p*
Conscientiousness				
Parcel 1	0.545	0.060	9.167	<0.000
Parcel 2	0.642	0.046	13.853	<0.000
Parcel 3	0.865	0.034	25.151	<0.000
Parcel 4	0.886	0.034	26.186	<0.000
Extraversion				
Parcel 1	0.668	0.048	14.051	<0.000
Parcel 2	0.639	0.049	13.141	<0.000
Parcel 3	0.848	0.035	24.374	<0.000
Parcel 4	0.774	0.039	19.944	<0.000
Mastery Goal Orientation				
Willing to select challenging work assignments to learn from	0.775	0.034	22.688	<0.000

(Table 16 continued)

Scale	β	S.E.	*t*	*p*
Look for opportunities to develop new skills and knowledge	0.657	0.045	14.661	<0.000
Enjoy challenging and difficult tasks at work to learn new skills	0.856	0.028	31.023	<0.000
Development of work ability is important enough to take risks	0.745	0.037	19.910	<0.000
Prefer work in situations requiring a high level of ability and talent	0.722	0.039	18.485	<0.000
Internal Locus of Control				
Parcel 1	0.314	0.074	4.254	<0.000
Parcel 2	0.854	0.114	7.511	<0.000
Parcel 3	0.667	0.110	6.062	<0.000
Parcel 4	0.539	0.081	6.631	<0.000
Parcel 5	0.457	0.083	5.535	<0.000

(Table 16 continued)

Scale	β	S.E.	*t*	*p*
Cognitive Ability				
Parcel 1	0.658	0.054	12.095	<0.000
Parcel 2	0.532	0.060	8.824	<0.000
Parcel 3	0.652	0.055	11.896	<0.000
Parcel 4	0.800	0.049	16.352	<0.000

the chi-square fit index, Standardized Root Mean Residual (SRMR), Root Mean Square Error of Approximation (RMSEA), Aikaike Information Criterion (AIC) and Comparative Fit Index (CFI) were examined. Definitions and cutoff values of the chi-square test and supplementary indexes are taken from Hu and Bentler (1999). The chi-square fit index directly compares the sample and model covariance matrices, and is the most widely used model fit statistic. A non-significant chi-square fit index indicates satisfactory overall model fit, though this statistic is inflated by large sample sizes (Thompson & Daniel, 1996). Absolute fit indices (SRMR and RMSEA) assess the degree of similarity between the a priori model and the sample data. SRMR is the average absolute value of the residual covariance matrix, and should be .08 or less to indicate good fit. As recommended by Hu and Bentler (1999), SRMR should be coupled with at least one other index in order to detect misspecification in measurement or structural model parameters. This is because the SRMR is most sensitive to detect structural model misspecifications (factor covariances), whereas other fit indices are more sensitive to measurement model misspecifications (factor loadings). Thus, RMSEA and CFI were also employed. The Root Mean Square Error of Approximation (RMSEA) estimates the error of approximation, or error due to the model as a simplification of reality. A RMSEA value of .05 or less would indicate good model fit. Incremental fit indices (such as the CFI) compare the hypothesized model with a restricted baseline model, typically a model of uncorrelated observed variables. CFI compares the model chi-square to the independence chi-square, and should be greater than 0.95 to indicate good fit. These supplementary fit indices were chosen together because of their common use in published empirical articles employing SEM, as well as the results of Monte Carlo simulations,

such as Fan, Thompson, and Wang's (1999) study, which indicated minimal influence of sample size and random variation. Each hypothesized partial mediation model was tested with and without the pre-training knowledge control variable. Pre-training knowledge is likely meaningfully related to many of the hypothesized individual difference variables and post-training learning outcomes. Spector and Brannick's (2011) advice regarding the effects of control variables "extraneous to the focal theory and hypotheses being tested" (p. 297) was followed. They advise to "do comparative tests with and without controls to show whether their addition has an effect on observed relationships among the substantive variables of interest to the study" (p.297). In order to investigate whether or not the hypothesized relationships are affected by pre-training knowledge, models were tested with and without the control variable. Model fit for each hypothesized model was assessed, and each model showed acceptable overall fit (see Table 17). Because of the high correlation between Excel experience and the pre-training knowledge test, these variables were correlated in the experience model. Each hypothesis was tested by examining standardized path coefficients

Hypothesis 1. Hypotheses 1a-1g stated that each individual difference would positively predict the usage of learner control. Tests of these hypotheses can be found in Table 18. Pre-training experience, openness, conscientiousness, and internal locus of control did not significantly predict the usage of sequence control, pace control, or content control, regardless of the pre-training knowledge control variable, failing to support Hypotheses 1a, b, c, and f. Extraversion did not significantly predict sequence

Table 17

Model Fit Statistics for Hypothesized Models, With and Without Pre-Training Knowledge Control Variable

Model	χ^2	df	p	CFI	AIC	RMSEA	SRMR
a. Experience and Pre-Training Knowledge	61.245	20	<0.000	0.937	8413.424	0.100	0.040
Without Pre-Training Excel Knowledge	26.223	17	0.071	0.982	7330.860	0.051	0.036
b. Openness and Pre-Training Knowledge	30.14	20	0.068	0.982	7667.573	0.049	0.033
Without Pre-Training Excel Knowledge	21.753	17	0.194	0.991	6535.420	0.037	0.031
c. Conscientiousness and Pre-Training Knowledge	29.931	19	0.053	0.984	7641.666	0.053	0.031
Without Pre-Training Excel Knowledge	21.485	16	0.161	0.991	6509.734	0.041	0.032
d. Extraversion and Pre-Training Knowledge	24.876	20	0.206	0.992	8025.238	0.034	0.034
Without Pre-Training Excel Knowledge	24.271	17	0.112	0.986	6899.322	0.045	0.035
e. Mastery Goal Orientation and Pre-Training Knowledge	47.142	29	0.018	0.977	7936.598	0.055	0.037
Without Pre-Training Excel Knowledge	35.213	25	0.084	0.986	6806.757	0.044	0.036
f. Internal Locus of Control and Pre-Training Knowledge	31.278	27	0.260	0.990	7975.512	0.028	0.047
Without Pre-Training Excel Knowledge	27.391	23	0.240	0.988	6843.495	0.030	0.048
g. Cognitive Ability and Pre-Training Knowledge	19.702	20	0.477	1.000	8132.204	0.000	0.028
Without Pre-Training Excel Knowledge	18.614	17	0.351	0.997	7001.705	0.021	0.029

Table 18

Standardized Path Coefficients for Usage of Learner Control on Individual Differences, for Models With and Without Pre-Training Knowledge Control Variable

	Sequence				Pace				Content			
Model	β	S.E.	*t*	*p*	β	S.E.	*t*	*p*	β	S.E.	*t*	p
With Pre-Training Knowledge												
a. Experience	0.062	0.097	0.637	0.524	0.149	0.094	1.590	0.112	0.043	0.104	0.416	0.677
Pre-K	0.021	0.091	0.229	0.819	-0.283	0.085	-3.325	0.001	-0.147	0.092	-1.595	0.111
b. Openness	0.147	0.080	1.835	0.067	-0.094	0.077	-1.221	0.222	-0.191	0.072	-2.630	0.009
Pre-K	0.041	0.073	0.552	0.581	-0.190	0.063	-3.028	0.002	-0.104	0.070	-1.480	0.139
c. Conscientiousness	0.058	0.074	0.790	0.430	0.024	0.076	0.320	0.749	-0.113	0.077	-1.474	0.140
Pre-K	0.062	0.074	0.835	0.404	-0.193	0.064	-3.001	0.003	-0.135	0.073	-1.841	0.066
d. Extraversion	-0.052	0.074	-0.694	0.488	0.155	0.073	2.131	0.033	0.116	0.069	1.685	0.092
Pre-K	0.056	0.075	0.745	0.456	-0.210	0.062	-3.397	0.001	-0.128	0.070	-1.832	0.067
e. MGO	0.154	0.069	2.230	0.026	0.086	0.078	1.106	0.269	-0.092	0.071	-1.299	0.194
Pre-K	0.040	0.071	0.558	0.577	-0.205	0.064	-3.212	0.001	-0.112	0.071	-1.573	0.116

(Table 18 continued)

Model	Sequence				Pace				Content			
	β	S.E.	*t*	*p*	β	S.E.	*t*	*p*	β	S.E.	*t*	p
f. Internal Locus	0.052	0.086	0.602	0.547	0.041	0.087	0.469	0.639	0.112	0.078	1.444	0.149
Pre-K	0.057	0.074	0.769	0.442	-0.194	0.063	-3.087	0.002	-0.111	0.071	-1.550	0.121
g. Cognitive Ability	0.246	0.086	2.868	0.004	-0.129	0.086	-1.502	0.133	-0.225	0.078	-2.871	0.004
Pre-K	-0.025	0.081	-0.307	0.759	-0.156	0.074	-2.126	0.033	-0.049	0.076	-0.639	0.523
Without Pre-Training Knowledge												
a. Experience	0.083	0.075	1.098	0.272	-0.009	0.075	-0.123	0.902	-0.052	0.077	-0.667	0.505
b. Openness	0.148	0.080	1.844	0.065	-0.105	0.076	-1.375	0.169	-0.195	0.072	-2.699	0.007
c. Conscientiousness	0.052	0.072	0.723	0.470	0.045	0.078	0.574	0.566	-0.103	0.077	-1.337	0.181
d. Extraversion	-0.050	0.074	-0.678	0.498	0.142	0.074	1.907	0.056	0.109	0.069	1.582	0.114
e. MGO	0.160	0.070	2.300	0.021	0.067	0.079	0.852	0.394	-0.104	0.071	-1.472	0.141
f. Internal Locus	0.047	0.086	0.550	0.582	0.057	0.087	0.653	0.514	0.122	0.077	1.583	0.113
g. Cognitive Ability	0.242	0.078	3.092	0.002	-0.178	0.080	-2.230	0.026	-0.242	0.072	-3.365	0.001

Note. Pre-K = Pre-training Knowledge.

control or content control. The relationship between extraversion and pace control was significant only when controlling for pre-training knowledge, but was non-significant when pre-training knowledge was not in the model. MGO significantly and positively predicted the usage of sequence control, regardless of the pre-training knowledge control variable, but did not significantly predict the usage of pace control or content control. Cognitive ability did not significantly predict content control. The significant relationship between cognitive ability and the usage of sequence control remained regardless of the pre-training knowledge control variable. The relationship between cognitive ability and pace control was significant only when pre-training knowledge was not controlled for; when pre-training knowledge served as a control variable, the relationship was not significant. The results with respect to extraversion, MGO, and cognitive ability provide limited support for Hypotheses 1d, e, and g.

Hypothesis 2. Hypothesis 2 stated that the usage of learner control would positively predict learning outcomes. Tests of this hypothesis can be found in Table 19 for post-training knowledge and 20 for post-training skill. Sequence control positively and significantly predicted both post-training knowledge and post-training skill across all individual difference models, regardless of controlling for pre-training knowledge. The usage of pace control significantly and negatively predicted post-training knowledge across all individual difference models. However, the relationship between pace control and post-training knowledge was only significant when pre-training knowledge was not used as a control variable. The usage of pace control did not significantly predict post-training skill. The usage of content remove control significantly and negatively predicted post-training knowledge across all individual difference models, regardless of controlling

Table 19

Standardized Path Coefficients for Post-Training Knowledge on Learner Control Usage, With and Without Pre-Training Knowledge Control Variable

	Sequence				Pace				Content			
Model	β	S.E.	*t*	*p*	β	S.E.	*t*	*p*	β	S.E.	*t*	*p*
With Pre-Training Knowledge												
Experience	0.238	0.062	3.873	0.000	-0.091	0.065	-1.397	0.162	-0.211	0.066	-3.214	0.001
Openness	0.237	0.062	3.834	0.000	-0.098	0.066	-1.491	0.136	-0.209	0.068	-3.084	0.002
Conscientiousness	0.238	0.061	3.889	0.000	-0.097	0.065	-1.496	0.135	-0.212	0.069	-3.090	0.002
Extraversion	0.232	0.061	3.796	0.000	-0.075	0.067	-1.122	0.262	-0.208	0.067	-3.121	0.002
MGO	0.243	0.061	3.969	0.000	-0.092	0.067	-1.360	0.174	-0.216	0.067	-3.220	0.001
Internal Locus	0.246	0.060	4.085	0.000	-0.100	0.066	-1.524	0.128	-0.200	0.067	-3.003	0.003
Cognitive Ability	0.179	0.060	2.972	0.003	-0.081	0.060	-1.357	0.175	-0.175	0.068	-2.577	0.010

(Table 19 continued)

	Sequence				Pace				Content			
Model	β	S.E.	*t*	*p*	β	S.E.	*t*	*p*	β	S.E.	*t*	*p*
Without Pre-Training Knowledge												
Experience	0.244	0.067	3.654	0.000	-0.187	0.074	-2.523	0.012	-0.201	0.079	-2.550	0.011
Openness	0.252	0.067	3.773	0.000	-0.184	0.074	-2.494	0.013	-0.203	0.083	-2.436	0.015
Conscientiousness	0.256	0.065	3.906	0.000	-0.172	0.072	-2.401	0.016	-0.220	0.082	-2.666	0.008
Extraversion	0.251	0.066	3.779	0.000	-0.171	0.074	-2.300	0.021	-0.205	0.080	-2.555	0.011
MGO	0.255	0.066	3.855	0.000	-0.185	0.075	-2.474	0.013	-0.206	0.082	-2.517	0.012
Internal Locus	0.266	0.067	3.992	0.000	-0.186	0.073	-2.537	0.011	-0.192	0.081	-2.360	0.018
Cognitive Ability	0.171	0.063	2.706	0.007	-0.139	0.069	-2.024	0.043	-0.160	0.081	-1.977	0.048

Table 20

Standardized Path Coefficients for Post-Training Skill on Learner Control Usage, With and Without Pre-Training Knowledge Control Variable

	Sequence				Pace				Content			
Model	β	S.E.	*t*	*p*	β	S.E.	*t*	*p*	β	S.E.	*t*	*p*
With Pre-Training Knowledge												
Experience	0.325	0.074	4.417	0.000	0.001	0.081	0.016	0.987	0.023	0.091	0.255	0.799
Openness	0.334	0.071	4.698	0.000	0.022	0.083	0.266	0.790	0.004	0.095	0.040	0.968
Conscientiousness	0.328	0.072	4.571	0.000	0.030	0.082	0.368	0.713	0.006	0.090	0.062	0.951
Extraversion	0.321	0.074	4.350	0.000	0.046	0.083	0.561	0.575	0.022	0.091	0.236	0.813
MGO	0.327	0.074	4.435	0.000	0.021	0.084	0.251	0.802	0.021	0.093	0.228	0.819
Internal Locus	0.326	0.075	4.360	0.000	0.022	0.083	0.269	0.788	0.018	0.094	0.196	0.844
Cognitive Ability	0.242	0.080	3.024	0.002	0.025	0.079	0.319	0.749	0.075	0.090	0.825	0.409

(Table 20 continued)

	Sequence				Pace				Content			
Model	β	S.E.	*t*	*p*	β	S.E.	*t*	*p*	β	S.E.	*t*	*p*
Without Pre-Training Knowledge												
Experience	0.324	0.074	4.371	0.000	-0.028	0.081	-0.352	0.725	0.028	0.092	0.307	0.759
Openness	0.339	0.072	4.691	0.000	-0.021	0.080	-0.262	0.793	0.010	0.097	0.099	0.921
Conscientiousness	0.332	0.072	4.612	0.000	-0.004	0.079	-0.055	0.956	0.003	0.091	0.037	0.971
Extraversion	0.328	0.075	4.396	0.000	-0.003	0.080	-0.040	0.968	0.026	0.093	0.281	0.779
MGO	0.330	0.074	4.454	0.000	-0.026	0.082	-0.311	0.756	0.028	0.095	0.297	0.766
Internal Locus	0.334	0.076	4.390	0.000	-0.021	0.080	-0.262	0.793	0.024	0.096	0.254	0.800
Cognitive Ability	0.237	0.081	2.940	0.003	0.005	0.075	0.072	0.943	0.082	0.092	0.892	0.372

for pre-training knowledge. The usage of content control did not significantly predict post-training skill. The results with respect to sequence control provide limited support for Hypothesis 2.

Hypothesis 3. Hypotheses 3a-g stated that the relationship between individual differences and learning outcomes will be mediated by the usage of learner control. Experience positively predicted both post-training knowledge and skill directly, but no indirect effects through the usage of learner control were significant (see Table 21 for post-training knowledge and 22 for post-training skill).

Openness did not significantly predict post-training knowledge directly, but total indirect effects through the usage of all learner control usage variables were significant. Significant total indirect effects were found regardless of controlling for pre-training knowledge. Thus, evidence of full mediation was found for the relationship between openness and post-training knowledge. Openness did not significantly predict post-training skill, directly nor indirectly (see Table 23 for post-training knowledge and 24 for post-training skill). Conscientiousness did not significantly predict post-training knowledge, directly or indirectly. Conscientiousness significantly and negatively predicted post-training skill when not controlling for pre-training knowledge. The direct relationship was not significant when controlling for pre-training knowledge. No indirect effects were significant for conscientiousness (see Table 25 for post-training knowledge and 26 for post-training skill). Extraversion significantly and negatively predicted post-training knowledge and skill, directly. These relationships were significant only when controlling for pre-training knowledge; when not controlling for pre-training knowledge, the relationships were non-significant. No significant indirect relationships were found.

Thus, no evidence of partial mediation was found (see Table 27 for post-training knowledge and 28 for post-training skill).

MGO and internal locus did not significantly predict post-training knowledge, directly or indirectly. Internal locus did not significantly predict post-training skill, directly or indirectly. MGO did not significantly predict post-training skill directly, but the indirect relationship through sequence control was positive and significant. Thus, no evidence of partial mediation was found, but evidence for full mediation through sequence control was found. This relationship was significant only when not controlling for pre-training knowledge (see Tables 29 and 30 for MGO and Tables 31 and 32 for internal locus).

Cognitive ability positively and significantly predicted post-training knowledge directly, regardless of controlling for pre-training knowledge. The indirect path through sequence control was positive and significant, the indirect path through content remove was negative and significant, and the total of all indirect effects was significant. Cognitive ability positively and significantly predicted post-training skill directly, regardless of controlling for pre-training knowledge. Indirect effects through sequence control only were positive and significant, regardless of the pre-training control variable. Thus, some support was found for a partial mediation relationship for both post-training knowledge and skill. The results with respect to cognitive ability provide partial support for Hypothesis 3g (see Table 33 for post-training knowledge and 34 for post-training skill).

Table 21

Standardized Path Loadings for Partial Mediation Test of Post-Training Knowledge on Experience and Pre-Training Knowledge

Model	β	S.E.	*t*	*p*
Experience With Pre-Training Knowledge				
Post-Training Knowledge on Experience				
Total Effects	-0.078	0.095	-0.820	0.412
Direct Effects	-0.070	0.083	-0.847	0.397
Total Indirect	-0.008	0.039	-0.202	0.840
Specific indirect: Sequence	0.015	0.024	0.606	0.545
Specific indirect: Pace	-0.014	0.015	-0.895	0.371
Specific indirect: Content	-0.009	0.023	-0.400	0.689
Post-Training Knowledge on Pre-Training Knowledge				
Total Effects	0.559	0.074	7.512	0.000
Direct Effects	0.498	0.071	6.972	0.000
Total Indirect	0.062	0.039	1.599	0.110
Specific indirect: Sequence	0.005	0.022	0.224	0.823
Specific indirect: Pace	0.026	0.021	1.200	0.230
Specific indirect: Content	0.031	0.023	1.355	0.175
Experience Without Pre-Training Knowledge				
Post-Training Knowledge on Experience				
Total Effects	0.237	0.074	3.190	0.001
Direct Effects	0.205	0.066	3.080	0.002
Total Indirect	0.032	0.035	0.913	0.361
Specific indirect: Sequence	0.020	0.020	1.022	0.307
Specific indirect: Pace	0.002	0.015	0.116	0.908
Specific indirect: Content	0.010	0.017	0.610	0.542

Table 22

Standardized Path Loadings for Partial Mediation Test of Post-Training Skill on Experience and Pre-Training Knowledge

Model	β	S.E.	*t*	*p*
Experience With Pre-Training Knowledge				
Post-Training Skill on Experience				
Total Effects	0.164	0.106	1.540	0.124
Direct Effects	0.142	0.099	1.437	0.151
Total Indirect	0.021	0.034	0.629	0.530
Specific indirect: Sequence	0.020	0.032	0.632	0.527
Specific indirect: Pace	0.000	0.015	0.013	0.989
Specific indirect: Content	0.001	0.011	0.095	0.924
Post-Training Skill on Pre-Training Knowledge				
Total Effects	0.142	0.089	1.587	0.113
Direct Effects	0.139	0.081	1.709	0.088
Total Indirect	0.003	0.038	0.079	0.937
Specific indirect: Sequence	0.007	0.030	0.226	0.821
Specific indirect: Pace	0.000	0.025	-0.015	0.988
Specific indirect: Content	-0.003	0.016	-0.207	0.836
Experience Without Pre-Training Knowledge				
Post-Training Skill on Experience				
Total Effects	0.227	0.080	2.837	0.005
Direct Effects	0.202	0.076	2.661	0.008
Total Indirect	0.026	0.026	0.967	0.334
Specific indirect: Sequence	0.027	0.025	1.071	0.284
Specific indirect: Pace	0.000	0.006	0.041	0.967
Specific indirect: Content	-0.001	0.009	-0.161	0.872

Table 23

Standardized Path Loadings for Partial Mediation Test of Post-Training Knowledge on Openness and Pre-Training Knowledge

Model	β	S.E.	*t*	*p*
Openness With Pre-Training Knowledge				
Post-Training Knowledge on Openness				
Total Effects	0.085	0.071	1.192	0.233
Direct Effects	0.001	0.068	0.015	0.988
Total Indirect	0.084	0.035	2.410	0.016
Specific indirect: Sequence	0.035	0.021	1.648	0.099
Specific indirect: Pace	0.009	0.011	0.818	0.413
Specific indirect: Content	0.040	0.020	1.959	0.050
Post-Training Knowledge on Pre-Training Knowledge				
Total Effects	0.507	0.045	11.181	0.000
Direct Effects	0.456	0.046	10.022	0.000
Total Indirect	0.050	0.032	1.588	0.112
Specific indirect: Sequence	0.010	0.018	0.537	0.591
Specific indirect: Pace	0.019	0.015	1.269	0.204
Specific indirect: Content	0.022	0.018	1.234	0.217
Openness Without Pre-Training Knowledge				
Post-Training Knowledge on Openness				
Total Effects	0.106	0.082	1.302	0.193
Direct Effects	0.010	0.080	0.131	0.896
Total Indirect	0.096	0.040	2.403	0.016
Specific indirect: Sequence	0.037	0.022	1.662	0.097
Specific indirect: Pace	0.019	0.017	1.140	0.254
Specific indirect: Content	0.040	0.022	1.760	0.078

Table 24

Standardized Path Loadings for Partial Mediation Test of Post-Training Skill on Openness and Pre-Training Knowledge

Model	β	S.E.	*t*	*p*
Openness With Pre-Training Knowledge				
Post-Training Skill on Openness				
Total Effects	-0.043	0.084	-0.518	0.605
Direct Effects	-0.090	0.084	-1.069	0.285
Total Indirect	0.046	0.032	1.430	0.153
Specific indirect: Sequence	0.049	0.028	1.728	0.084
Specific indirect: Pace	-0.002	0.010	-0.201	0.841
Specific indirect: Content	-0.001	0.019	-0.039	0.969
Post-Training Skill on Pre-Training Knowledge				
Total Effects	0.231	0.066	3.504	0.000
Direct Effects	0.222	0.062	3.585	0.000
Total Indirect	0.009	0.031	0.285	0.776
Specific indirect: Sequence	0.014	0.025	0.542	0.588
Specific indirect: Pace	-0.004	0.017	-0.248	0.804
Specific indirect: Content	0.000	0.012	-0.033	0.974
Openness Without Pre-Training Knowledge				
Post-Training Skill on Openness				
Total Effects	-0.034	0.086	-0.394	0.693
Direct Effects	-0.084	0.087	-0.974	0.330
Total Indirect	0.050	0.033	1.507	0.132
Specific indirect: Sequence	0.050	0.029	1.742	0.082
Specific indirect: Pace	0.002	0.011	0.209	0.835
Specific indirect: Content	-0.002	0.020	-0.095	0.924

Table 25

Standardized Path Loadings for Partial Mediation Test of Post-Training Knowledge on Conscientiousness and Pre-Training Knowledge

Model	β	S.E.	*t*	*p*
Conscientiousness With Pre-Training Knowledge				
Post-Training Knowledge on Conscientiousness				
Total Effects	0.025	0.069	0.356	0.722
Direct Effects	-0.011	0.068	-0.162	0.871
Total Indirect	0.036	0.032	1.104	0.270
Specific indirect: Sequence	0.014	0.018	0.756	0.450
Specific indirect: Pace	-0.002	0.009	-0.261	0.794
Specific indirect: Content	0.024	0.020	1.226	0.220
Post-Training Knowledge on Pre-Training Knowledge				
Total Effects	0.514	0.047	10.965	0.000
Direct Effects	0.452	0.049	9.188	0.000
Total Indirect	0.062	0.033	1.890	0.059
Specific indirect: Sequence	0.015	0.018	0.811	0.417
Specific indirect: Pace	0.019	0.015	1.291	0.197
Specific indirect: Content	0.029	0.019	1.471	0.141
Conscientiousness Without Pre-Training Knowledge				
Post-Training Knowledge on Conscientiousness				
Total Effects	-0.048	0.079	-0.609	0.543
Direct Effects	-0.077	0.076	-1.002	0.316
Total Indirect	0.028	0.038	0.753	0.452
Specific indirect: Sequence	0.013	0.019	0.690	0.490
Specific indirect: Pace	-0.008	0.015	-0.525	0.599
Specific indirect: Content	0.023	0.021	1.097	0.272

Table 26

Standardized Path Loadings for Partial Mediation Test of Post-Training Skill on Conscientiousness and Pre-Training Knowledge

Model	β	S.E.	*t*	*p*
Conscientiousness With Pre-Training Knowledge				
Post-Training Skill on Conscientiousness				
Total Effects	-0.130	0.083	-1.563	0.118
Direct Effects	-0.149	0.083	-1.784	0.074
Total Indirect	0.019	0.027	0.702	0.483
Specific indirect: Sequence	0.019	0.025	0.752	0.452
Specific indirect: Pace	0.001	0.007	0.112	0.911
Specific indirect: Content	-0.001	0.012	-0.051	0.960
Post-Training Skill on Pre-Training Knowledge				
Total Effects	0.211	0.067	3.150	0.002
Direct Effects	0.198	0.063	3.159	0.002
Total Indirect	0.014	0.031	0.443	0.658
Specific indirect: Sequence	0.020	0.025	0.812	0.417
Specific indirect: Pace	-0.006	0.017	-0.340	0.734
Specific indirect: Content	-0.001	0.014	-0.053	0.958
Conscientiousness Without Pre-Training Knowledge				
Post-Training Skill on Conscientiousness				
Total Effects	-0.158	0.084	-1.879	0.060
Direct Effects	-0.175	0.085	-2.058	0.040
Total Indirect	0.017	0.025	0.687	0.492
Specific indirect: Sequence	0.017	0.028	0.605	0.545
Specific indirect: Pace	0.000	0.007	-0.028	0.978
Specific indirect: Content	0.000	0.012	-0.029	0.977

Table 27

Standardized Path Loadings for Partial Mediation Test of Post-Training Knowledge on Extraversion and Pre-Training Knowledge

Model	β	S.E.	*t*	*p*
Extraversion With Pre-Training Knowledge				
Post-Training Knowledge on Extraversion				
Total Effects	-0.213	0.060	-3.521	0.000
Direct Effects	-0.165	0.055	-3.015	0.003
Total Indirect	-0.048	0.029	-1.648	0.099
Specific indirect: Sequence	-0.012	0.018	-0.666	0.506
Specific indirect: Pace	-0.012	0.012	-0.944	0.345
Specific indirect: Content	-0.024	0.016	-1.460	0.144
Post-Training Knowledge on Pre-Training Knowledge				
Total Effects	0.527	0.043	12.147	0.000
Direct Effects	0.471	0.045	10.521	0.000
Total Indirect	0.055	0.031	1.799	0.072
Specific indirect: Sequence	0.013	0.018	0.729	0.466
Specific indirect: Pace	0.016	0.015	1.040	0.298
Specific indirect: Content	0.027	0.018	1.499	0.134
Extraversion Without Pre-Training Knowledge				
Post-Training Knowledge on Extraversion				
Total Effects	-0.175	0.071	-2.454	0.014
Direct Effects	-0.116	0.064	-1.795	0.073
Total Indirect	-0.059	0.033	-1.782	0.075
Specific indirect: Sequence	-0.013	0.020	-0.645	0.519
Specific indirect: Pace	-0.024	0.017	-1.427	0.154
Specific indirect: Content	-0.022	0.017	-1.287	0.198

Table 28

Standardized Path Loadings for Partial Mediation Test of Post-Training Skill on Extraversion and Pre-Training Knowledge

Model	β	S.E.	*t*	*p*
Extraversion With Pre-Training Knowledge				
Post-Training Skill on Extraversion				
Total Effects	-0.155	0.073	-2.114	0.035
Direct Effects	-0.148	0.071	-2.085	0.037
Total Indirect	-0.007	0.028	-0.247	0.805
Specific indirect: Sequence	-0.017	0.024	-0.675	0.500
Specific indirect: Pace	0.007	0.014	0.496	0.620
Specific indirect: Content	0.002	0.013	0.192	0.848
Post-Training Skill on Pre-Training Knowledge				
Total Effects	0.240	0.066	3.634	0.000
Direct Effects	0.235	0.062	3.768	0.000
Total Indirect	0.005	0.031	0.175	0.861
Specific indirect: Sequence	0.018	0.025	0.730	0.465
Specific indirect: Pace	-0.010	0.019	-0.520	0.603
Specific indirect: Content	-0.003	0.014	-0.203	0.839
Extraversion Without Pre-Training Knowledge				
Post-Training Skill on Extraversion				
Total Effects	-0.137	0.075	-1.832	0.067
Direct Effects	-0.123	0.072	-1.702	0.089
Total Indirect	-0.014	0.028	-0.512	0.609
Specific indirect: Sequence	-0.017	0.025	-0.658	0.510
Specific indirect: Pace	0.000	0.013	-0.035	0.972
Specific indirect: Content	0.003	0.013	0.222	0.824

Table 29

Standardized Path Loadings for Partial Mediation Test of Post-Training Skill on Mastery Goal Orientation and Pre-Training Knowledge

Model	β	S.E.	*t*	*p*
Mastery Goal Orientation With Pre-Training Knowledge				
Post-Training Knowledge on MGO				
Total Effects	-0.004	0.059	-0.059	0.953
Direct Effects	-0.053	0.052	-1.028	0.304
Total Indirect	0.050	0.034	1.467	0.142
Specific indirect: Sequence	0.038	0.020	1.878	0.060
Specific indirect: Pace	-0.008	0.010	-0.749	0.454
Specific indirect: Content	0.020	0.018	1.122	0.262
Post-Training Knowledge on Pre-Training Knowledge				
Total Effects	0.512	0.044	11.560	0.000
Direct Effects	0.460	0.046	10.072	0.000
Total Indirect	0.053	0.032	1.634	0.102
Specific indirect: Sequence	0.010	0.018	0.543	0.587
Specific indirect: Pace	0.019	0.015	1.222	0.222
Specific indirect: Content	0.024	0.018	1.319	0.187
Mastery Goal Orientation Without Pre-Training Knowledge				
Post-Training Knowledge on MGO				
Total Effects	0.046	0.069	0.665	0.506
Direct Effects	-0.004	0.060	-0.066	0.948
Total Indirect	0.050	0.040	1.255	0.210
Specific indirect: Sequence	0.041	0.022	1.866	0.062
Specific indirect: Pace	-0.012	0.017	-0.745	0.457
Specific indirect: Content	0.021	0.018	1.163	0.245

Table 30

Standardized Path Loadings for Partial Mediation Test of Post-Training Skill on Mastery Goal Orientation and Pre-Training Knowledge

Model	β	S.E.	*t*	*p*
Mastery Goal Orientation With Pre-Training Knowledge				
Post-Training Skill on Mastery Goal Orientation				
Total Effects	0.030	0.078	0.387	0.699
Direct Effects	-0.020	0.080	-0.249	0.804
Total Indirect	0.050	0.026	1.923	0.054
Specific indirect: Sequence	0.050	0.026	1.959	0.050
Specific indirect: Pace	0.002	0.010	0.184	0.854
Specific indirect: Content	-0.002	0.011	-0.181	0.856
Post-Training Skill on Pre-Training Knowledge				
Total Effects	0.228	0.065	3.540	0.000
Direct Effects	0.222	0.062	3.586	0.000
Total Indirect	0.006	0.031	0.204	0.838
Specific indirect: Sequence	0.013	0.024	0.547	0.585
Specific indirect: Pace	-0.004	0.018	-0.236	0.813
Specific indirect: Content	-0.002	0.013	-0.188	0.851
Mastery Goal Orientation Without Pre-Training Knowledge				
Post-Training Skill on Mastery Goal Orientation				
Total Effects	0.052	0.082	0.637	0.524
Direct Effects	0.004	0.083	0.048	0.961
Total Indirect	0.048	0.027	1.787	0.074
Specific indirect: Sequence	0.053	0.027	1.984	0.047
Specific indirect: Pace	-0.002	0.009	-0.186	0.852
Specific indirect: Content	-0.003	0.012	-0.243	0.808

Table 31

Standardized Path Loadings for Partial Mediation Test of Post-Training Knowledge on Internal Locus of Control and Pre-Training Knowledge

Model	β	S.E.	*t*	*p*
Internal Locus With Pre-Training Knowledge				
Post-Training Knowledge on Internal Locus				
Total Effects	-0.081	0.085	-0.957	0.339
Direct Effects	-0.067	0.075	-0.903	0.366
Total Indirect	-0.014	0.030	-0.455	0.649
Specific indirect: Sequence	0.013	0.022	0.590	0.555
Specific indirect: Pace	-0.004	0.011	-0.385	0.701
Specific indirect: Content	-0.022	0.018	-1.272	0.203
Post-Training Knowledge on Pre-Training Knowledge				
Total Effects	0.506	0.046	11.115	0.000
Direct Effects	0.450	0.046	9.752	0.000
Total Indirect	0.056	0.032	1.749	0.080
Specific indirect: Sequence	0.014	0.019	0.748	0.454
Specific indirect: Pace	0.019	0.015	1.310	0.190
Specific indirect: Content	0.022	0.017	1.290	0.197
Internal Locus Without Pre-Training Knowledge				
Post-Training Knowledge on Internal Locus				
Total Effects	-0.112	0.090	-1.242	0.214
Direct Effects	-0.090	0.080	-1.132	0.258
Total Indirect	-0.021	0.036	-0.597	0.550
Specific indirect: Sequence	0.013	0.024	0.534	0.593
Specific indirect: Pace	-0.011	0.018	-0.597	0.550
Specific indirect: Content	-0.023	0.019	-1.230	0.219

Table 32

Standardized Path Loadings for Partial Mediation Test of Post-Training Skill on Internal Locus of Control and Pre-Training Knowledge

Model	β	S.E.	*t*	*p*
Internal Locus of Control With Pre-Training Knowledge				
Post-Training Skill on Internal Locus of Control				
Total Effects	0.032	0.090	0.352	0.725
Direct Effects	0.012	0.089	0.132	0.895
Total Indirect	0.020	0.032	0.615	0.539
Specific indirect: Sequence	0.017	0.029	0.587	0.557
Specific indirect: Pace	0.001	0.008	0.110	0.912
Specific indirect: Content	0.002	0.013	0.159	0.874
Post-Training Skill on Pre-Training Knowledge				
Total Effects	0.233	0.064	3.610	0.000
Direct Effects	0.220	0.061	3.642	0.000
Total Indirect	0.012	0.031	0.397	0.691
Specific indirect: Sequence	0.019	0.025	0.744	0.457
Specific indirect: Pace	-0.004	0.017	-0.250	0.803
Specific indirect: Content	-0.002	0.013	-0.159	0.874
Internal Locus of Control Without Pre-Training Knowledge				
Post-Training Skill on Internal Locus of Control				
Total Effects	0.018	0.091	0.201	0.841
Direct Effects	0.001	0.089	0.008	0.993
Total Indirect	0.018	0.033	0.536	0.592
Specific indirect: Sequence	0.016	0.030	0.534	0.593
Specific indirect: Pace	-0.001	0.009	-0.134	0.894
Specific indirect: Content	0.003	0.014	0.213	0.831

Table 33

Standardized Path Loadings for Partial Mediation Test of Post-Training Knowledge on Cognitive Ability and Pre-Training Knowledge

Model	β	S.E.	*t*	*p*
Cognitive Ability With Pre-Training Knowledge				
Post-Training Knowledge on Cognitive Ability				
Total Effects	0.412	0.062	6.672	0.000
Direct Effects	0.318	0.063	5.070	0.000
Total Indirect	0.094	0.028	3.347	0.001
Specific indirect: Sequence	0.044	0.022	2.051	0.040
Specific indirect: Pace	0.010	0.012	0.870	0.384
Specific indirect: Content	0.039	0.019	2.064	0.039
Post-Training Knowledge on Pre-Training Knowledge				
Total Effects	0.381	0.058	6.511	0.000
Direct Effects	0.364	0.054	6.774	0.000
Total Indirect	0.017	0.027	0.610	0.542
Specific indirect: Sequence	-0.004	0.015	-0.288	0.773
Specific indirect: Pace	0.013	0.012	1.075	0.282
Specific indirect: Content	0.009	0.015	0.569	0.569
Cognitive Ability Without Pre-Training Knowledge				
Post-Training Knowledge on Cognitive Ability				
Total Effects	0.531	0.063	8.428	0.000
Direct Effects	0.426	0.068	6.296	0.000
Total Indirect	0.105	0.030	3.546	0.000
Specific indirect: Sequence	0.041	0.020	2.095	0.036
Specific indirect: Pace	0.025	0.016	1.503	0.133
Specific indirect: Content	0.039	0.022	1.785	0.074

Table 34

Standardized Path Loadings for Partial Mediation Test of Post-Training Skill on Cognitive Ability and Pre-Training Knowledge

Model	β	S.E.	*t*	*p*
Cognitive Ability With Pre-Training Knowledge				
Post-Training Skill on Cognitive Ability				
Total Effects	0.448	0.078	5.751	0.000
Direct Effects	0.408	0.085	4.793	0.000
Total Indirect	0.040	0.031	1.291	0.197
Specific indirect: Sequence	0.060	0.027	2.197	0.028
Specific indirect: Pace	-0.003	0.013	-0.252	0.801
Specific indirect: Content	-0.017	0.024	-0.689	0.491
Post-Training Skill on Pre-Training Knowledge				
Total Effects	0.099	0.072	1.381	0.167
Direct Effects	0.113	0.070	1.617	0.106
Total Indirect	-0.014	0.024	-0.557	0.577
Specific indirect: Sequence	-0.006	0.020	-0.297	0.766
Specific indirect: Pace	-0.004	0.014	-0.282	0.778
Specific indirect: Content	-0.004	0.009	-0.392	0.695
Cognitive Ability Without Pre-Training Knowledge				
Post-Training Skill on Cognitive Ability				
Total Effects	0.479	0.070	6.878	0.000
Direct Effects	0.443	0.079	5.623	0.000
Total Indirect	0.036	0.031	1.169	0.243
Specific indirect: Sequence	0.057	0.025	2.286	0.022
Specific indirect: Pace	-0.001	0.015	-0.064	0.949
Specific indirect: Content	-0.020	0.025	-0.779	0.436

CHAPTER V

DISCUSSION

This study investigated a model of individual differences, learner control usage, and learning outcomes. Based on the results of the analysis, several hypotheses were partially supported, but the majority were unsupported, and most of the theoretical models were largely unsupported. Overall, Hypothesis 1 stated that each individual difference would positively predict the usage of all learner control features. After investigating Hypotheses 1a-g, results indicated that only three of the seven hypothesized individual differences predicted certain types of learner control usage. Participants higher in extraversion used more pace control, but only when controlling for pre-training knowledge. This is consistent with prior literature regarding differential behavior in training due to personality (Barrick & Mount, 1991; Goldberg, 1993). Participants higher in MGO used more sequence control, and participants higher in cognitive ability used more sequence control and used less pace control (only without controlling for pre-training knowledge). These relationships are consistent with past research regarding the effects of MGO and cognitive ability on training behavior (Button, Matthieu, & Zajac, 1996; Ree & Earles, 1991).

No individual difference investigated predicted the use of content remove control. It is possible that the lack of significant findings for content is due to the measurement of content remove control is due to the measurement of that construct (explained further in the next paragraph). Experience, conscientiousness, openness, and internal locus of control did not significantly predict the usage of any type of learner control features. The lack of support for the prediction of learner control usage for these traits stands in

opposition to previous findings that these trainee characteristics should predict increased interaction with training programs and explain variability in training behavior (Barrick & Mount, 1991; Goldberg, 1993; Noe & Schmitt; 1986; Ones, Viswesvaran, & Dilchert, 2005). An explanation for the lack of prediction of learner control usage could be lower engagement or motivation and thus lower activity in training in this particular sample. Future research should continue to examine individual differences and behavior during training with greater assurances of high motivation.

Hypothesis 2 stated that the usage of learner control would positively predict learning outcomes. This hypothesis was supported for the usage of sequence control, but not for the usage of pace or content remove control. Those who used more sequence control performed better on both the knowledge and skill post-tests. It seems that participants who went out of order during training learned more. It could be argued that the usage of sequence control is an indicator of being more active in training, and those who are more active in training tend to learn more (Campbell & Kuncel, 2002). Based on the operational definition of sequence control, these results may also include effects from seeing material more than one time (i.e., with use of the "Previous" button). Future research should examine this variable separately for the usage of the navigational menu to view whole sections out of order and the usage of the "Previous" button to view pages multiple times.

Those who used more pace control actually performed worse on the post-training knowledge test, when not controlling for pre-training knowledge. Contrary to the hypothesized effects of pace control usage, the usage of pace control negatively predicted post-training knowledge, but not above and beyond the effects of pre-training knowledge.

It appears that deciding to spend more time or less time than average on each training section may actually be harmful to learning. An explanation for this finding could be that learners without prior knowledge should have spent more time per section but instead went through training too quickly. The current study measured pace control as mean deviation time instead of total time, in an attempt to capture the usage of pace control specifically, and not just total time spent on training. However, empirical evidence for time training has been fairly consistent in training research; spending more time on training positively predicts learning (Fisher & Ford, 1998), so it is possible that effects from total time clouded the measurement of pace control. Based on the findings from the current study, future investigations should identify an alternate measurement approach for pace control that does not exhibit such undesirable measurement characteristics. Those who removed more content also performed worse on the knowledge test, and thus viewing more content of the training was associated with increased learning. It appears that many participants who should have viewed all of the slides of training did not, and this harmed learning. Unfortunately, the low variability in content add control made it impossible to model in tests of hypotheses. Future research should investigate one single content construct that combines both amount of training content viewed and amount of additional content added to training.

Lastly, Hypothesis 3 stated that the usage of learner control partially mediated the relationship between each individual difference and learning. Hypotheses 3a-f were unsupported; however, the cognitive ability partial mediation model (Hypothesis 3g) was partially supported. The usage of sequence and content control partially mediated the relationship between cognitive ability and post-training knowledge. The usage of

sequence control partially mediated the relationship between cognitive ability and post-training skill. Direct effects to learning were non-significant for internal locus of control. Indirect effects to learning were non-significant for experience, extraversion, conscientiousness, and internal locus of control. Thus, key requirements of partial mediation were not met for these individual differences. Interestingly, openness did not directly predict post-training knowledge, but indirectly predicted post-training knowledge through all types of control. Similarly, MGO did not directly predict post-training skill, but indirectly predicted skill through sequence control. It appears that the relationship between these differences and learning outcomes is fully mediated; variance in learning is explained by these individual differences only through the usage of learner control features. This was the first study to investigate the usage of learner control as a partial mediator in the relationship between individual trainee characteristics and learning outcomes, and only the effect of cognitive ability was supported.

Limitations

This study was the first investigation using mTurk Workers to study online training, and the first to define and measure the usage of learner control features. Most studies regarding learner control use student samples (see Kraiger & Jerden, 2007) but the current participants were adults, most of whom were currently employed. This sample much more closely matched to a sample of employees than an undergraduate sample, in terms of age, occupation status, and education level. However, this was not a sample of employees from one organization, and it is unknown how these results would transfer to a sample of employees from one organization. Because Microsoft Excel is a software program for personal use, typically used for calculating values and

storing/organizing data, these results would probably generalize well to a sample of employees. Quite a few Workers reported being very satisfied and glad to have a training program on Excel in their open-ended feedback. Several Workers, however, voiced concerns that the incentive was much too small for the amount of time that it took to complete the HIT. It is possible that these reactions impacted the results of the study, and additional studies of Worker reactions to incentives would be interesting to examine in the future, especially in relation to learner control usage and learning outcomes.

Second, the results from the pilot study informed certain choices made about the full study, including incentives and time allotted for Workers to finish the study. These decisions were not based on any theory, but were driven solely by the results from the pilot study. It is possible that the incentives given to participants do not closely match to the incentives an organization gives for finishing a training program, whether it is a requirement or an opportunity outside of the job requirements.

Similarly, the definitions and measurement of learner control usage had to be adapted during data cleaning. The initial plan for the learner control mediator variable was a unidimensional learner control factor, with measured indicators for each type of control. However, the data for each type of learner control was severely non-normal, and had to be transformed or polytomized in order to be analyzed in the hypothesized models. Further, it was clear from the data that there is not a unidimensional learner control usage factor, and we currently lack both theory to explain these distributions and distributions of these behaviors from prior research for comparison.

In general, participants do not use very much learner control when it is given to them. It is possible that sufficient incentives were not used for the study, and that the

usage of learner control would increase in a different sample. For those participants who are not intrinsically motivated to learn, or do not need to learn for work or school, it is conceivable that \$2.50 was not an adequate incentive for the time and effort it takes to learn to use Microsoft Excel.

Lastly, there were two limitations in the analysis of the data and measurement of one of the outcome variables. First, there was a substantial amount of missing data for the skill outcome variable. The post-test Excel file was submitted by participants through the website after the training program. However, several Workers uploaded training workbooks, instead of the final training skill activity. Because these workbooks were partially completed when downloaded by the Worker, they did not evidence actual skill gains by participants and were thus excluded from analysis. Several participants skipped uploading the skill measure at all. The researcher's email address and directions to email the file appeared on the upload page, and participants were directed to email if the upload feature was not functioning. Although several participants submitted Excel files to the researcher during the pilot study, it is possible that relatively few Workers emailed because they interpreted this as a violation of Amazon's policies (which forbid the collection of email addresses) or as an invasion of privacy. No participants emailed completed skilled measures to the researcher in the main study. It seems that this may be a difficult-to-avoid side effect of online data collection in which an uploaded assignment is necessary. Researchers should utilize another type of check on this type of data. The second limitation was that in the interest of time, all skill activities were rated by one researcher, potentially reducing reliability of that measure. Although internal consistency

was acceptable for the skill measure, multiple raters and a calculation of interrater reliability will be used in the future to follow best practices in research.

Implications

Based on these initial results, there are implications for both research and practice. A great deal of research over many years has found that cognitive ability is a positive and robust predictors of many job-related outcomes, including training performance and job performance (Kuncel, Hezlett, & Ones, 2004; Hunter & Hunter, 1984). The results of the current study support these past findings, and extend them to a learning environment with a high level of learner control. It appears that those who are higher in cognitive ability use learner control features the most and learn the most from training programs with high levels of learner control. Differences in learning can be attributed to both direct effects of cognitive ability and indirect effects of learner behavior. It is not surprising, given that the training environment in this study had a low level of external influences that this trait significantly impacted important outcomes. There were no outside influences such as instructors, classmates, or job requirements to complete this training program, which would normally influence behavior during learning.

Further, the usage of sequence control stood out as a positive predictor of learning outcomes. This indicates a type of control to be explored further in research, and may be used as a first step in implementing learner control in an actual employee training setting. Based on the current study's results, providing and using sequence control appears to be a feature that provides benefit to trainees' learning. Instructing trainees to utilize sequence control as a way to improve learning may provide a benefit to trainees.

Future Directions

The present study examined several constructs and relationships relevant to employee training and technology in the workplace. However, several questions were raised that were not addressed within the scope of this study, which relate to data collection on the internet, the measurement of learner control usage, and the generalizability of these results to employees in an organization.

This study was the first to compare a sample of undergraduate students and mTurk Workers in a training study. Age, motivation, time training, and learning outcomes were compared between the two samples. Although the samples differed significantly in age, motivation, and learning, they did not differ in the time they spent training. It would be interesting to compare the samples on other variables relevant to training. It is unknown whether unmeasured variables differed in the undergraduate sample, including individual differences such as cognitive ability and personality, as well as behavior during training.

This was the first study to quantify and measure the usage of learner control. Although a measurement strategy was decided upon prior to data collection, the training data appeared to be a bit different than initially anticipated. First, the option to add content was added to the training program to give participants the option to receive more information regarding topics that were especially interesting or difficult. For the current sample, very few participants added any content, and those who did, did not add very much. It is possible that employees completing a job-relevant training would use this feature much more, but a Mechanical Turk sample earning a few dollars to complete a training program did not. It is possible that participants with a higher motivation to learn

more information from training would add more content. Sequence control was measured for the first time in a training program by using navigation deviation. The measurement of sequence control included any use the Back button and the navigational menu. It is unclear which, or both, led to the positive learning outcomes. The way this variable was measured also contains some elements of repeating content; participants who used the Back button after moving forward were seeing slides more than once. After examining the raw training data, it appeared that many participants who used sequence control often were actually viewing many of the slides multiple times. It is possible that seeing content multiple times may be a separate and important construct to study when studying behavior in a learner controlled training environment, in addition to the other types of control measured already.

This study was also a first step in examining several individual differences to predict the usage of learner control features and learning outcomes. It is unknown whether the majority of the hypotheses were unsupported because of the method of measuring learner control variables, unseen error in measuring online behavior, or because the relationships are simply not there for the current sample. An in-person study examining off-task attention and behavior not tracked by the training website may shed some light in this area. This study did show that learner control features are not used unanimously when they are given to learners. In order to test the hypothesized model, only one training program version with high learner control was used. In the future, a comparison of a training program with high and low learner control assigned at random should be conducted to examine differences in behavior during training, reactions to training, and learning outcomes.

Lastly, the data collected from mTurk Workers appeared to reflect an older, more motivated, more educated, and already employed sample of people when compared to undergraduate students. But it is unknown whether the mTurk sample differs in these areas to an actual sample of employees from one organization. It is also unknown whether employees from one organization may use learner control differently, or that the conclusions drawn from the mTurk sample will transfer to a sample of employees. It is possible that other factors could impact behavior during training and learning from an online program. These other factors could include pressure to complete training from a manager, superior, or peers, compensation for training, or learning requirements for the job. An examination of organizational factors influencing behavior and learning outcomes in a high learner control training program is warranted.

Conclusion

This study attempted to investigate individual differences and the usage of learner control to explain differences in learning outcomes. Although the hypotheses were generally unsupported, this effort represents a first step in understanding how learners use learner control, and how this in turn affects learning outcomes in online training programs. Because flexible online training programs are becoming more and more prevalent in the workplace, further work in this area will help organizations best implement online training methods for their employees.

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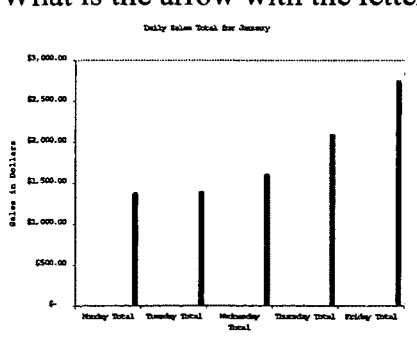
APPENDIX A

PRE-TRAINING MEASURES

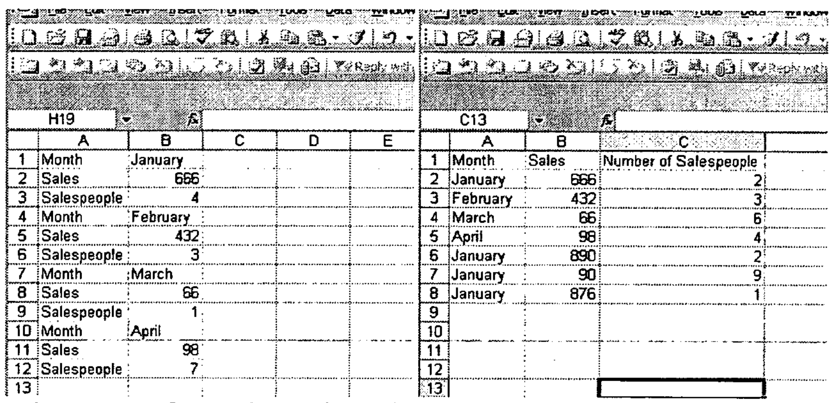
Excel Knowledge Pre-Test

1. This dialog box allows you to add buttons to the Quick Access toolbar:
    A. Excel Options
    B. Add Buttons
    C. Customize Excel
    D. Fast Access
2. What is the first step for performing many basic Excel functions?
    A. copying data
    B. saving data
    C. highlighting data
    D. grouping data
3. Which of the following statements is false?
    A. A standard Excel workbook has 3 sheets
    B. You can use the arrow keys on the keyboards to move between worksheets
    C. Ctrl+C can be used to copy data
    D. Pressing this button will undo the last command:
4. After highlighting a group of cells, how do you define them as a range?
    A. Formulas tab >> Apply Name >> Define Name
    B. Formulas tab >> Define Name >> Apply Name
    C. Formulas tab >> Define Name >> Define Name
    D. Formulas tab >> Apply Name >> Apply Name
5. Which dialogue box do you use to write an If function?
    A. Function Arguments
    B. Function Cells
    C. Format Arguments
    D. Format Cells
6. #/DIV0! Indicates:
    A. The formula you typed contains a letter
    B. An incorrect argument is included in the denominator of the formula
    C. The formula is trying to divide by zero
    D. The argument in the denominator refers to a cell that does not exist
7. What is the arrow with the letter *a* pointing to?



A. category axis
B. value axis
C. chart area
D. plot area

8. Which of the following is the correct sequence to add an axis title below the chart?
   A. Layout tab>>Axis Titles>>Primary Vertical Axis Title>>Title Below Axis
   B. Format tab>>Axis Titles>>Primary Vertical Axis Title>>Title Below Axis
   C. Layout tab>>Axis Titles>>Primary Horizontal Axis Title>>Title Below Axis
   D. Format tab>>Axis Titles>>Primary Horizontal Axis Title>>Title Below Axis



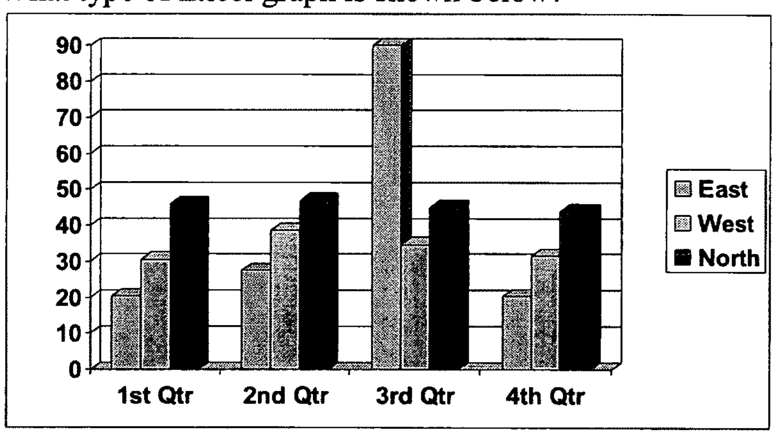
H19

	A	B	C	D	E
1	Month	January			
2	Sales	666			
3	Salespeople	4			
4	Month	February			
5	Sales	432			
6	Salespeople	3			
7	Month	March			
8	Sales	66			
9	Salespeople	1			
10	Month	April			
11	Sales	98			
12	Salespeople	7			
13					

C13

	A	B	C
1	Month	Sales	Number of Salespeople
2	January	666	2
3	February	432	3
4	March	66	6
5	April	98	4
6	January	890	2
7	January	90	9
8	January	876	1
9			
10			
11			
12			
13			

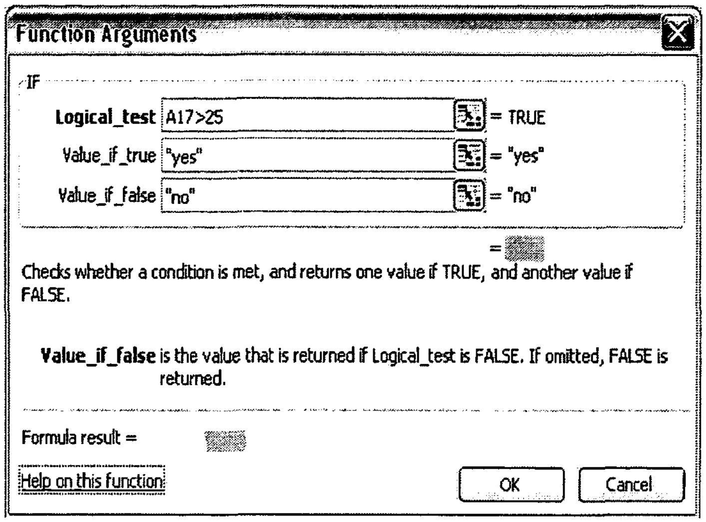
9. What type of Excel graph is shown below?



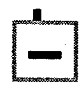
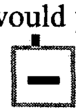
   A. Column chart
   B. Bar chart
   C. Line chart
   D. Area chart

10. In what programming language are macros recorded?
   A. Visual Basic for Programs
   B. Visual Basic for Applications
   C. Visual Basic for Microsoft
   D. Visual Basic for Macros

11. Which type of workbook already has macros enabled?
    A. xlsx
    B. xlsm
    C. xltx
    D. mxls
12. Which of the following is associated with columns?
    A. Numbers
    B. Letters
    C. Letters and Numbers
    D. None of the above
13. Where will Excel tell you it is done saving data?
    A. Quick Access toolbar
    B. user interface Ribbon
    C. status bar
    D. task pane
14. You want to copy and paste new data from one row into another using keyboard shortcuts. What is the correct order of steps?
    A. Highlight data, Ctrl+C, Click in new row, Ctrl+V
    B. Highlight data, Ctrl+C, Click in new row, Ctrl+P
    C. Highlight data, Ctrl+P, Click in new row, Ctrl+C
    D. Highlight data, Ctrl+V, Click in new row, Ctrl+C
15. How do you save your workbook?
    A. Ctrl+S
    B. Ctrl+V
    C. Office button, Save as
    D. Both A and C
16. What does the If function allow you to create?
    A. Conditional Format
    B. Conditional Formula
    C. Conditional Task
    D. Conditional Edit
17. Which error code tells you that the formula contains text that Excel does not recognize?
    A. #####
    B. #VALUE!
    C. #NAME?
    D. #REF!
18. Cell A17 has the number $59.70 in it. If you clicked on cell C18 and then entered the following information in to the function arguments dialogue box, what would you expect to see in cell C18?

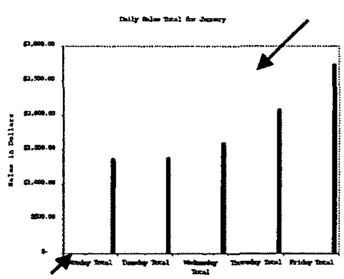


A. 25
B. yes
C. no
D. >25

19. What does the following button.... allow you to do when viewing levels? 
    A. Show detail
    B. Hide detail
    C. Show a level
    D. Hide a level
20. You organized your data using levels and now, only the grand total is left. What button would you click on to make all the data reappear?
    A. 
    B.  correct answer
    C. 

    D. 

21. What is the arrow with the letter *b* pointing to?



A. plot area
B. chart area

C. graph area
D. axis area

22. What does the Chart Styles section of the Design tab allow you to do?
    A. Allows you to add a chart title and axis titles
    B. Allows you to change the type of chart you want
    C. Adds, removes, or positions labels on the chart
    D. Changes the color and design of your chart
23. Which of the following opens Microsoft Visual Basic Editor?
    A. Alt + F9
    B. Alt + F10
    C. Alt + F11
    D. Alt + F12
24. You have already opened the Excel options dialog box and now want to add a macro to the Quick Access toolbar. What is the first step?
    A. Select the Macro you want
    B. Select Macros in the Choose Commands From box
    C. Click the Add button
    D. None of the above

Cognitive Ability Measures

Verbal Reasoning

Directions: For questions 1-5, select one entry for each blank from the corresponding column of choices. Fill all blanks in the way that best completes the text.

1. In the 1950s, the country's inhabitants were_______: most of them knew very little about foreign countries.
   a. partisan
   b. erudite
   c. insular
   d. cosmopolitan
   e. imperturbable

2. It is his dubious distinction to have proved what nobody would think of denying, that Romero at the age of sixty-four writes with all the characteristics of _______.
   a. maturity
   b. fiction
   c. inventiveness
   d. art
   e. brilliance

3. The (i) _______ nature of classical tragedy in Athens belies the modern image of tragedy: in the modern view tragedy is austere and stripped down, its representations of ideological and emotional conflicts so superbly compressed that there's nothing (ii) _______ for time to erode.

   Blank (i)

a. unadorned
b. harmonious
c. multifaceted

Blank (ii)
a. inalienable
b. exigent
c. extraneous

4. To the untutored eye the tightly forested Ardennes hills around Sedan look quite (i) _______, (ii) _______ place through which to advance a modern army; even with today's more numerous and better roads and bridges, the woods and the river Meuse form a significant (iii) _______.
   Blank (i)
   a. impenetrable
   b. inconsiderable
   c. uncultivated

   Blank (ii)
   a. a makeshift
   b. an unpropitious
   c. an unremarkable

   Blank (iii)
   a. resource
   b. impediment
   c. passage

5. Room acoustics design criteria are determined according to the room's intended use. Music, for example, is best (i) _______ in spaces that are reverberant, a condition that generally makes speech less (ii) _______. Acoustics suitable for both speech and music can sometimes be created in the same space, although the result is never perfect, each having to be (iii) _______ to some extent.
   Blank (i)
   a. controlled
   b. appreciated
   c. employed

   Blank (ii)
   a. abrasive
   b. intelligible
   c. ubiquitous

   Blank (iii)
   a. compromised
   b. eliminated

c. considered

Directions: For questions 6 and 7, select the two answer choices that when used to complete the sentence blank, fit the meaning of the sentence as a whole and produce completed sentences that are alike in meaning.

6. Early critics of Emily Dickinson's poetry mistook for simplemindedness the surface of artlessness that in fact she constructed with such ________.
   a. astonishment
   b. craft
   c. cunning
   d. innocence
   e. naïveté
   f. vexation

7. While in many ways their personalities could not have been more different—she was ebullient where he was glum, relaxed where he was awkward, garrulous where he was _______ —they were surprisingly well suited.
   a. solicitous
   b. munificent
   c. irresolute
   d. laconic
   e. fastidious
   f. taciturn

Quantitative Reasoning

Directions: For Questions 8 and 9, compare Quantity A and Quantity B, using the given information. You must determine which quantity is larger, if either.

1. A certain recipe requires 3/2 cups of sugar and makes 2 dozen cookies. (1 dozen = 12) Quantity A is the amount of sugar required for the same recipe to make 30 cookies. Quantity B is 2 cups.
   a. Quantity A is greater.
   b. Quantity B is greater.
   c. The two quantities are equal.
   d. The relationship cannot be determined from the information given.

2. 6 < x < 7 AND y = 8. Quantity A is x/y. Quantity B is 0.85.
   a. Quantity A is greater.
   b. Quantity B is greater.
   c. The two quantities are equal.
   d. The relationship cannot be determined from the information given.

Directions: For Questions 10 and 11, choose the one correct answer.

3. $7x + 3y = 12$ AND $3x + 7y = 6$. If x and y satisfy the system of equations above, what is the value of $x - y$?
   a. 2/3
   b. 3/2
   c. 1
   d. 4
   e. 6

1. Of the 750 participants in a professional meeting, 450 are female and 1/2 of the female and 1/4 of the male participants are less than thirty years old. If one of the participants will be randomly selected to receive a prize, what is the probability that the person selected will be less than thirty years old?
   a. 1/8
   b. 1/3
   c. 3/8
   d. 2/5
   e. 3/4

2. The total number of recording titles distributed by music distributors L and M is 9,300. The number of recording titles distributed by L is 7,100, and the number of recording titles distributed by M is 5,200. Which of the following statements must be true? **Select ALL such statements.**
   a. More than half of the titles distributed by L are also distributed by M.
   b. More than half of the titles distributed by M are also distributed by L.
   c. No titles are distributed by both L and M.

Mastery Goal Orientation Scale

Please select the response that best matches your agreement or disagreement with the following items (1= strongly disagree, 2=disagree, 3=neither agree nor disagree, 4=agree, 5=strongly agree):

1. I am willing to select a challenging work assignment that I can learn a lot from.
2. I often look for opportunities to develop new skills and knowledge.
3. I enjoy challenging and difficult tasks at work where I'll learn new skills.
4. For me, development of my work ability is important enough to take risks.
5. I prefer to work in situations that require a high level of ability and talent.

Locus of Control

For each of the following statements, please indicate the degree to which you agree or disagree. (1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, 5 = strongly agree)

1. There really is no such thing as "luck."
2. It is impossible for me to believe that chance or luck plays an important role in my life.
3. Many of the unhappy things in people's lives are partly due to bad luck.
4. People are lonely because they don't try to be friendly.

5. Most misfortunes are the result, of lack of ability, ignorance, laziness, or all three.
6. People who can't get others to like them don't understand how to get along with others.
7. By taking an active part in political and social affairs the people can control world events.
8. The average citizen can have an influence in government decisions.
9. It is difficult for people to have much control over the things politicians do in office.
10. Who gets to be the boss often depends on who was lucky enough to be in the right place first.
11. Many times I feel that I have little influence over the things that happen to me.
12. Unfortunately, an individual's worth often passes unrecognized no matter how hard he tries.
13. One of the major reasons why we have wars is because people don't take enough interest in politics.
14. There will always be wars, no matter how hard people try to prevent them.
15. No matter how hard you try, some people just don't like you.

Big Five Personality Questionnaire

How Accurately Can You Describe Yourself?
Please use this list of common human traits to describe yourself as accurately as possible. Describe yourself as you see yourself at the present time, not as you wish to be in the future. Describe yourself as you are generally or typically, as compared with other persons you know of the same sex and of roughly your same age.

Next to each trait, please type the number indicating how accurately that trait describes you, using the following rating scale:

1. Extremely Inaccurate, 2. Moderately Inaccurate, 3. Neither Accurate Nor Inaccurate, 4. Moderately Accurate, or 5. Extremely Accurate

1. Bashful
2. Bold
3. Careless
4. Cold
5. Complex
6. Cooperative
7. Creative
8. Deep
9. Disorganized
10. Efficient
11. Energetic
12. Envious
13. Extraverted
14. Fretful
15. Harsh
16. Imaginative
17. Inefficient
18. Intellectual
19. Jealous
20. Kind
21. Moody
22. Organized
23. Philosophical
24. Practical
25. Quiet
26. Relaxed
27. Rude
28. Shy
29. Sloppy
30. Sympathetic

31. Systematic
32. Talkative
33. Temperamental
34. Touchy
35. Uncreative
36. Unenvious
37. Unintellectual
38. Unsympathetic
39. Warm
40. Withdrawn

Biographical Data, Experience, and Preference for Learner Control

1. What is your age?
2. What is your highest level of education attained?
   a. Some high school
   b. High School diploma
   c. Some college
   d. Associate's degree
   e. Bachelor's degree
   f. Master's Degree
   g. Doctoral Degree
3. Are you currently enrolled in school?
   a. What is your year in school?
   b. What is your GPA?
4. What were your quantitative and verbal SAT scores, combined (if applicable)?
5. What was your SAT writing score (if applicable)?
6. What was your ACT score (if applicable)?
7. What is your race and/or ethnicity?
   a. White
   b. African American
   c. Hispanic
   d. Asian
   e. American Indian/Pacific Islander
   f. Other
8. What is your gender?
   a. Male
   b. Female
   c. Other
9. Are you currently employed?
   a. What is your occupation?
   b. How many hours do you work per week?
   c. Are you a part-time or full-time employee?
   d. Do you consider this job to be a long-term occupation (your career)?
10. How familiar are you with using Microsoft Excel?
   a. I am not at all familiar at all with Microsoft Excel.
   b. I am slightly familiar with using Microsoft Excel
   c. I am moderately familiar with Microsoft Excel
   d. I am very familiar with Microsoft Excel
   e. I am extremely familiar with Microsoft Excel
11. How important is using your current knowledge of Microsoft Excel in your job?

a. Not at all important
b. Slightly important
c. Moderately important
d. Very important
e. Extremely important

12. How important is using your current knowledge of Microsoft Excel for reasons other than work?
a. Not at all important
b. Slightly important
c. Moderately important
d. Very important
e. Extremely important

13. How often do you use Microsoft Excel for work?
a. Never
b. Less than once a month
c. Monthly
d. Weekly
e. Daily

14. How often do you use Microsoft Excel for reasons other than work?
a. Everyday
b. Several times a week
c. Several times a month
d. Several times a year
e. Never

15. Have you ever taken a course on Microsoft Excel?
a. What was the duration of the course?
b. When did you take the course?

Please rate how much you agree with the following statements:

16. When I am learning something new, I like to have the option to go over the information more than once.
a. Strongly disagree
b. Disagree
c. Neither agree nor disagree
d. Agree
e. Strongly agree

17. When I am learning something new, I like to have the option to go as slowly or as quickly as I want.
a. Strongly disagree
b. Disagree
c. Neither agree nor disagree
d. Agree
e. Strongly agree

18. When I am learning something new, I like to be able to skip information I already know.
a. Strongly disagree

b. Disagree
c. Neither agree nor disagree
d. Agree
e. Strongly agree

19. If you could choose the format of this Microsoft Excel training course, which of the following options would you want to have (please check all that apply):
a. Ability to navigate both forwards and backwards through the course.
b. Ability to move through the course at my own pace.
c. Ability to choose the specific Microsoft Excel topics covered in the course.
d. None of the above, I would like to go through the course as it has been designed, with no control over the navigation, pace, or content of the course.

APPENDIX B

PRE-TRAINING INSTRUCTIONS

Thank you for completing the surveys. Next, you will receive the Microsoft Excel training. This training covers a number of topics related to using Microsoft Excel. The training is highly interactive, so please **download this Excel file now** so you can follow along as you go through the training.

Following the training, you will be asked to complete a short Excel activity and a brief series of surveys.

During the training program, you will have control over several aspects of the course.

First, you will be able to control the pace of the course; you can spend as much or as little time as you think you need on each topic. Second, you will be able to control the sequence of the course. You can use the "Previous" and "Next" buttons at any time to go back to a previous page or go forward to the next page. There will also be a navigational menu on the left side of the training webpage at all times so you can complete the topics in any order you would like. The page number of the training that you are currently on will appear at the bottom of each page. Third, you will be able to control the content of the course. You are not required to view all of the training pages, but the knowledge test after the training will cover material from all of the topics in the training. It is suggested that you review all topics you are not familiar with in order to learn the most from this course. You will also be able to add content to the training program by clicking "More info on this topic" in the Navigation menu.

Please watch this video for more information about the training program before you begin:

Transcript of Training Instructions Video

Hi. Thanks for completing the pre-training surveys. Next, you'll receive the Microsoft Excel training program, and it looks like this. On the right hand side will be the information and then at all times on the left hand side, you'll have a navigation menu. You can see that there are four modules in this training program and within each module are several different subtopics. You have control over three aspects of this training program. First, you have control over the pacing. You can decide which sections or section you would like to spend more time on (if it's something especially interesting or difficult for you). You can also spend less time on certain parts that you already know a lot about or that are easy for you. Next, you have control over the sequence of this program. You can go ahead and use this Next button to get to all of the different pages in the training in order. You can always use the previous button as well, and this will take you to the previous page that you were just on. You can also go through the training in any different order that makes sense to you. So for example, if it makes more sense to you to learn about Graphs, you can go ahead and do this topic before you do Analyzing

with Excel. You can use this menu to complete the training in any order you like. Lastly, you have control over the content of this course. You're not required to view all 190 pages of the course, so if there's a topic or subtopic you already know a lot about, you don't have to visit those pages. You do have the option of adding more content, so if there's a topic or subtopic that you're really interested in or may be a bit confused about, you can always get more information on it. If you're looking at If-Then statements here on page 75, and you want more information, then you can always just use this link below- - it says More Info on this Topic. This will lead you to an outside webpage and there will be more information on it. This one's a video about If-Then statements. Then when you're done, you can just close that out and you'll be right back to the training where you were before. At the end of the training, on page 190, there will be a link for you to get to the Microsoft Excel Activity. Or you can get there at any time on the Navigation menu by clicking this link, Finish Training and move on to the Excel activity.

I'm really interested in how people use these different features, so I'd like you to really think about which feature or features will help you to best learn, and then use those features. Okay, thanks for listening. You can go ahead and start the training program now.

APPENDIX C

OUTLINE OF TRAINING PROGRAM

A. Module 1:
   a. Basic terminology
   b. Basic functions
   c. Customizing the quick access toolbar
   d. Working with your data
B. Module 2:
   a. Calculations
   b. Filters
   c. Recording and summarizing
C. Module 3:
   a. Making a chart
   b. Chart terminology
   c. Customizing a chart
D. Module 4:
   a. Macros
   b. Looking up information
   c. Publishing information on the web
   d. Collaborating with colleagues

APPENDIX D

POST-TRAINING MEASURES

Excel Knowledge Post-Test

Excel knowledge post-test is identical to Excel knowledge pre-test (Appendix B).

Excel Skill Post-Test

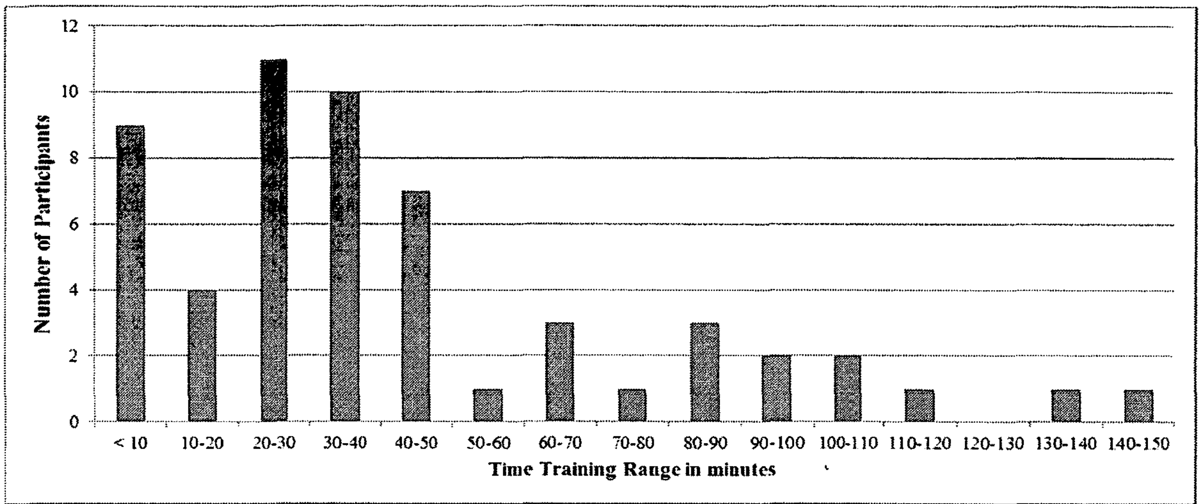
Download the dataset provided. Using the data labeled "February," create a range for morning, afternoon, and evening sales. Report the sum of the morning, afternoon, and evening sales. Also, report the summed sales for each day of the week. Create a chart to report sales by day of the week and another chart to report sales based on time of day. Customize your chart so that it includes labels and so that is easy to understand. Finally, create a macro to remove the color coding found in the chart. When you have finished save your file and name it with your unique id number and the date (example: 123456.11.21.10). Upload the file by clicking "Browse," selecting the Excel file you just saved, and clicking on "Submit." You will then be taken to a webpage containing the final questionnaire.

February Sales Report												
	9:00 AM	10:00 AM	11:00 AM	12:00 PM	1:00 PM	2:00 PM	3:00 PM	4:00 PM	5:00 PM	6:00 PM	7:00 PM	8:00 PM
Monday	$8.00	$8.00	$43.00	$18.95	$92.00	$0.00	$33.95	$54.00	$44.95	$83.95	$19.95	$43.00
Tuesday	$4.00	$10.00	$33.95	$18.95	$87.00	$12.00	$0.00	$10.00	$57.00	$57.95	$64.95	$0.00
Wednesday	$13.00	$3.00	$0.00	$15.00	$49.00	$0.00	$28.00	$33.95	$44.95	$69.95	$54.55	$0.00
Thursday	$0.00	$5.00	$7.00	$30.00	$50.00	$0.00	$28.00	$44.95	$19.95	$0.00	$28.00	$50.65
Friday	$12.00	$19.85	$85.00	$44.00	$59.00	$40.00	$10.00	$174.35	$200.00	$215.75	$83.95	$65.35
Monday	$0.00	$7.00	$18.95	$59.95	$56.00	$22.00	$32.00	$0.00	$65.85	$64.95	$18.00	$44.95
Tuesday	$0.00	$11.00	$22.00	$0.00	$42.00	$20.00	$41.95	$54.00	$39.00	$102.30	$34.95	$0.00
Wednesday	$5.00	$0.00	$8.00	$13.00	$45.00	$41.00	$44.95	$18.95	$34.95	$44.70	$18.95	$45.00
Thursday	$5.00	$7.75	$68.00	$13.85	$0.00	$59.95	$18.95	$27.75	$69.95	$0.00	$0.00	$45.50
Friday	$9.00	$8.00	$98.00	$22.00	$49.00	$33.00	$0.00	$133.80	$90.00	$90.00	$44.95	$54.65
Monday	$6.00	$0.00	$57.95	$18.00	$83.00	$0.00	$44.15	$64.95	$18.95	$69.95	$69.95	$56.45
Tuesday	$5.00	$0.00	$48.00	$15.00	$76.00	$27.00	$39.95	$46.75	$47.00	$98.05	$34.95	$12.50
Wednesday	$0.00	$8.00	$9.00	$32.00	$40.00	$26.35	$18.95	$31.15	$54.00	$79.95	$58.00	$37.35
Thursday	$0.00	$0.00	$0.00	$34.00	$65.00	$0.00	$18.95	$34.95	$14.95	$41.95	$18.95	$45.00
Friday	$10.00	$15.00	$87.00	$28.00	$63.00	$53.00	$69.95	$69.95	$0.00	$67.95	$54.00	$67.00
Monday	$10.00	$9.00	$21.00	$26.00	$38.00	$62.55	$57.95	$164.35	$54.00	$82.40	$69.95	$29.95
Tuesday	$0.00	$11.00	$0.00	$27.00	$42.00	$31.00	$44.85	$65.00	$69.95	$164.35	$47.65	$97.65
Wednesday	$0.00	$12.00	$0.00	$69.95	$67.00	$23.00	$18.00	$18.00	$87.55	$34.95	$54.00	$73.35
Thursday	$10.00	$14.00	$44.95	$0.00	$76.00	$21.00	$12.50	$14.95	$44.95	$39.95	$57.95	$74.65
Friday	$13.00	$27.95	$18.00	$45.00	$45.00	$43.00	$59.95	$18.95	$44.95	$118.95	$0.00	$85.75

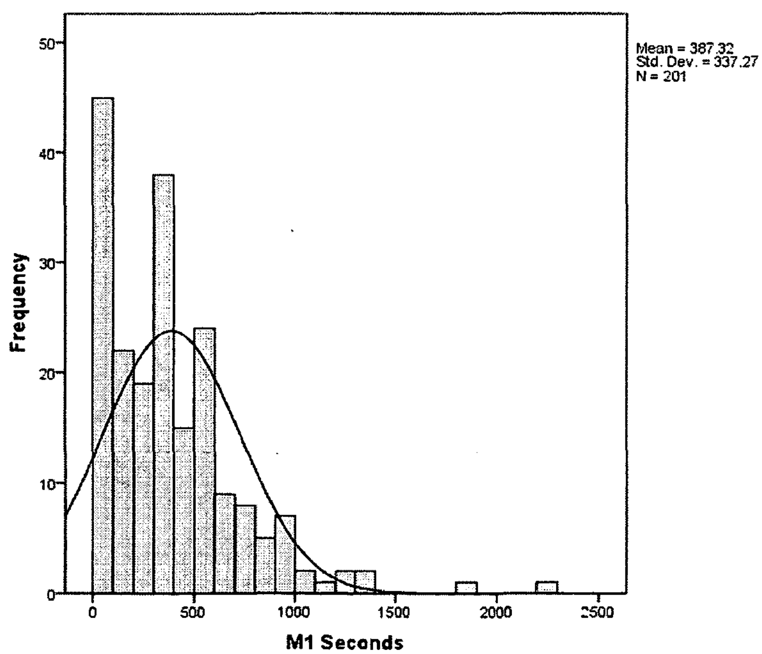
APPENDIX E

HISTOGRAMS OF SKEWED DATA

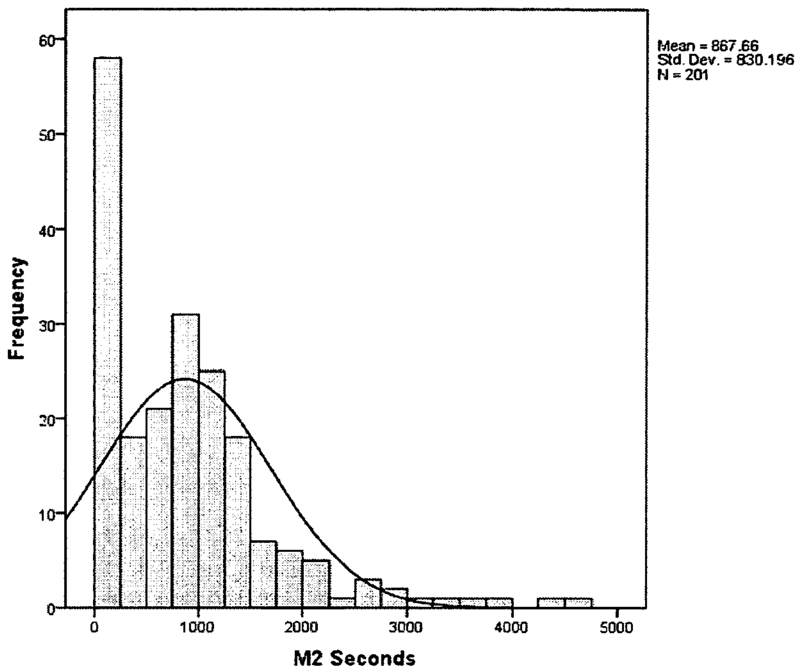
Pilot Study Total Training Time



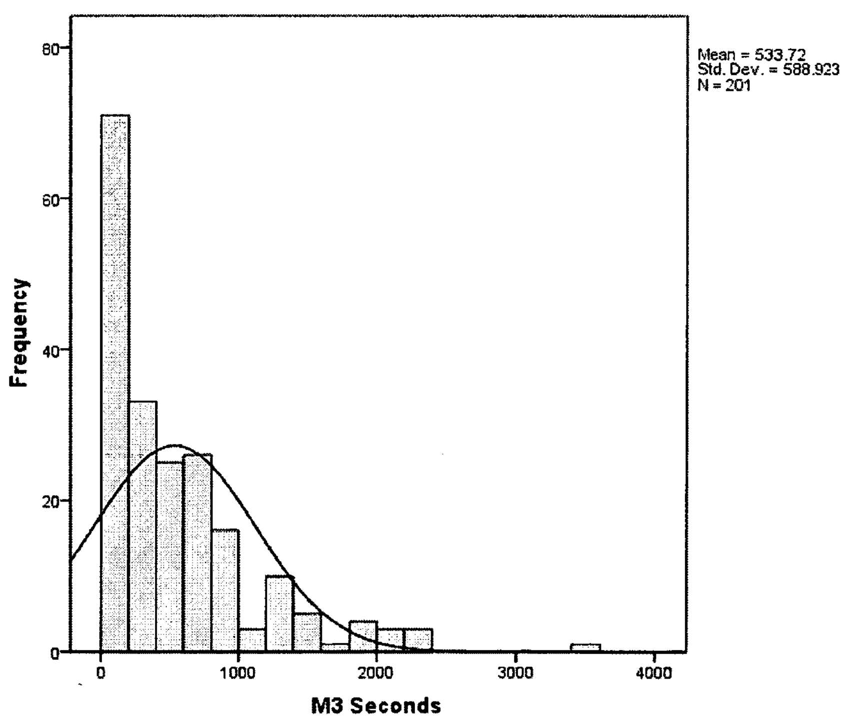
Full Study Training Time – Module 1



Full Study Training Time – Module 2



Full Study Training Time – Module 3



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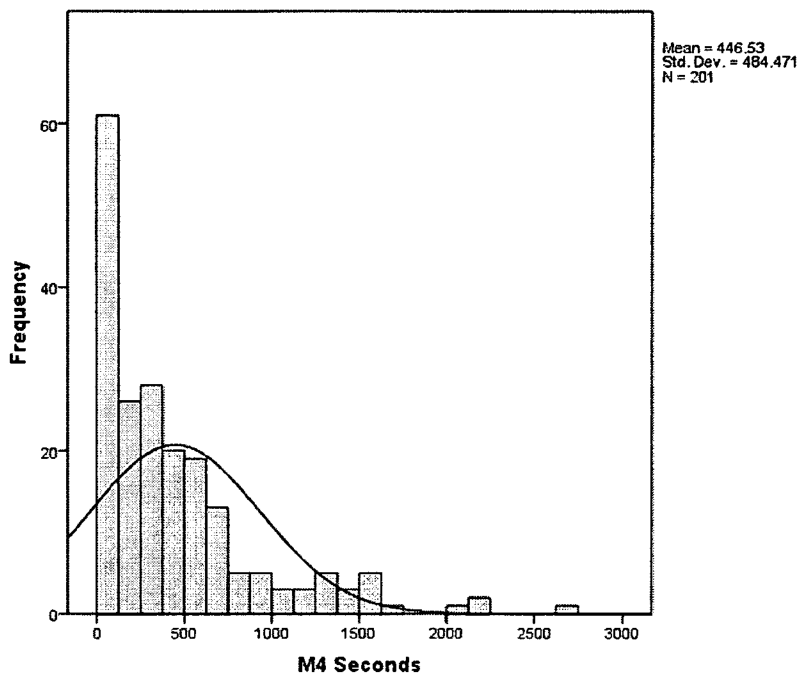
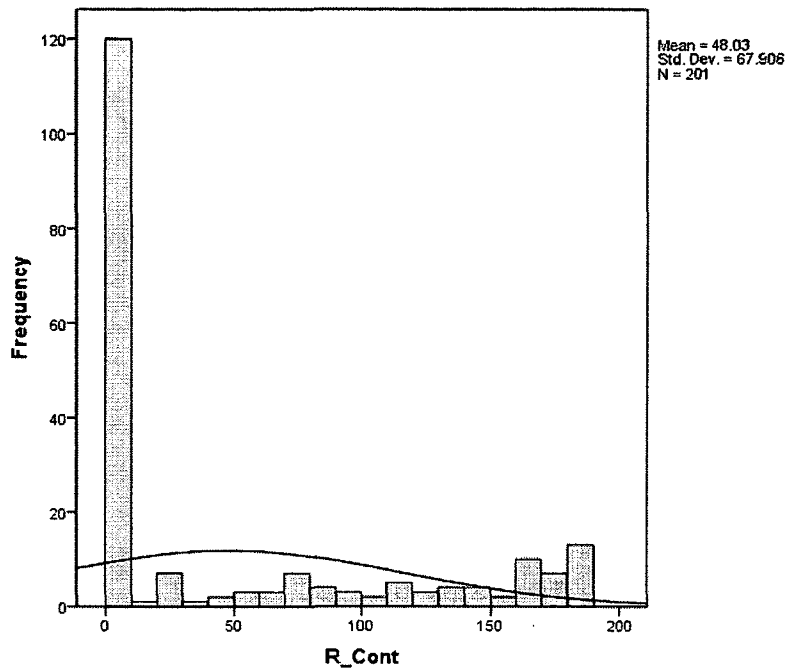
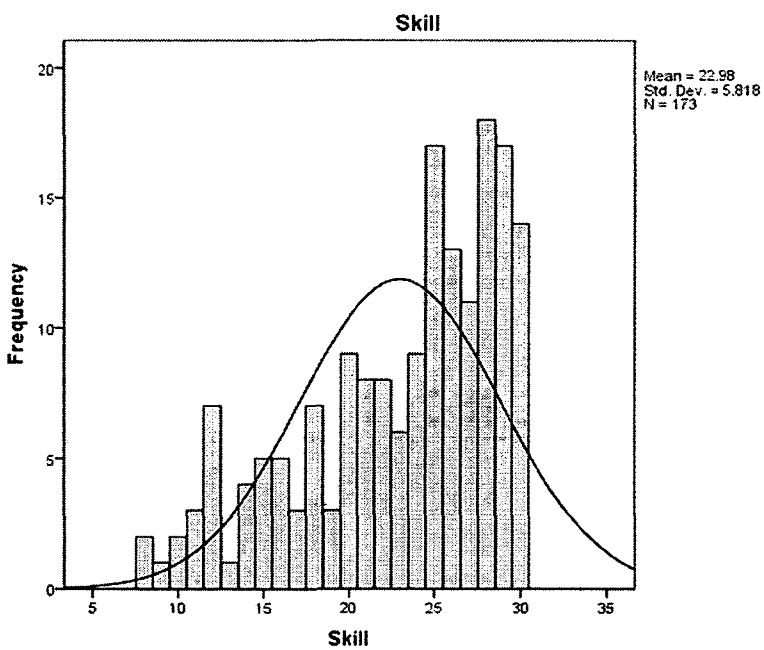


Full Study Content Remove



Full Study Skill



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POSTERS AND PRESENTATIONS

Landers, R. N., Reddock, C. M., Callan, R. C. & Cavanaugh, K. J. (2011, October). The evolving role of the Internet for employees and students. Symposium presented at the fall 2011 conference of the Virginia Psychological Association.

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