Spring 2018

Investigating Application of the Self-explanation Learning Strategy During an Instructional Simulation

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INVESTIGATING APPLICATION OF THE SELF-EXPLANATION LEARNING STRATEGY DURING AN INSTRUCTIONAL SIMULATION

by

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

DOCTOR OF PHILOSOPHY

INSTRUCTIONAL DESIGN & EDUCATIONAL TECHNOLOGY

OLD DOMINION UNIVERSITY
May 2018

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ABSTRACT

INVESTIGATING APPLICATION OF THE SELF-EXPLANATION LEARNING STRATEGY DURING AN INSTRUCTIONAL SIMULATION

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Computer-based simulations effectively support the acquisition of scientific knowledge when combined with a guided learning approach. Active learning drives complex cognitive processes that enable the integration of new information with existing knowledge. The iCAP (Interactive, Constructive, Active, Passive) Framework provides a conceptual model to describe different types of active learning. Computer-based simulations fit neatly within this framework. Similarly, self-explanation is a generative learning strategy that fits within this framework. Promoting self-explanation using instructional prompts is an effective method for driving application of the strategy. This study compared three combinations of self-explanation prompt and learner activity (closed prompts – overt activity, open prompts – overt activity, open prompts - non-overt activity) when using an instructional simulation to acquire knowledge related to scientific principles. Outcome measures included pretest-posttest comparisons, cognitive load, and self-efficacy.

Results of the study indicated that closed prompts were more effective in driving application of the self-explanation learning strategy and learning outcomes when used within the context of an instructional simulation. Findings were less conclusive in terms of the type of activity (overt / non-overt). Only the closed prompts – overt activity treatment supported the attainment of greater learning outcomes when compared to the other treatments. No significant difference in learning outcomes was found for the open prompts – overt activity, and the open prompts – non-overt activity. In relation to cognitive load, no significant difference was revealed between treatments. In relation to self-efficacy, no significant difference was revealed between treatments or between measures recorded pre-instruction and post-instruction.

Keywords: Self-Explanation, Generative Learning, iCAP, Computer Simulations, Self-Efficacy, Cognitive Load.

Dedicated to Luc & Lucy.

Follow your curiosity. Reflect on what you learn. Don’t be afraid to ask for or offer help. Remember that you write your life story (so make it a great story!) Be nice to others ☺. Stay forever young.

ACKNOWLEDGEMENTS

First and foremost I would like to thank each of my dissertation committee members for their support throughout this process. Dr. Whittecar and Dr. Enderson, your participation on the committee added rigor, expertise, and broadened the scope of the study. My commitment to supporting the development of more effective educational tools related to mathematics and the sciences is stronger as a result.

Dr. Watson, throughout my time as your advisee, you have been a model for the best academic behaviors. You provided me with room to explore and discover the essential skills and knowledge required to successfully complete the program. When I got lost along the way you gave me clear direction. When I ran into challenges you provided encouragement. You were always available (early mornings, late nights, and weekends!). At some point in the future, I hope to lead students through this process, and my aspiration is to do so by applying this same approach to the standards that you have set.

Without the assistance of Dr. Chris Miles and Mariam Abdelhamid I would not have been able to collect the data for this study. Thank you so much for going out of your way to support me through this process.

At work, two of my managers, Rich Benner and Dr. Larry Israelite, provided a foundational support critical to enabling me to complete the process. Your interest in my progress over the past few years provided continuous motivation. Thank you.

A special word of gratitude to Dr. Tim & Dr. Susanna McMahon. Tim passed away before I began this process, but his encouragement was central to getting me started. We miss you.

Throughout my life, my parents have been my central influence. Being able to recognize what “good” looks like was easy when I saw it every day. The late nights at the kitchen table helping me with my homework paid off. Thanks for being who you both are, and thanks for always being with me along the way. Words simply cannot say enough.

Finally, when I started this project it was myself and Iris. Since then we have added Luc and Lucy. Iris, from helping me with my statistics homework (with a newborn baby in your lap), to proofreading and correcting multiple versions of this dissertation, you have been my constant source of support and inspiration. The three of you make up my universe. As we close this chapter, we open another. I can’t wait to continue the story.

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CHAPTER I

BACKGROUND

Introduction

In recent years, a proliferation of instructional simulations have been made available to educators via online repositories such as the PhET project by the University of Colorado, Boulder (https://phet.colorado.edu/), Molecular Workbench by the Concord Consortium (http://mw.concord.org/modeler/), and Gizmos by Explore Learning (https://www.explorelearning.com/index.cfm?method=cCorp.dspAbout). Computer-based simulations have been shown to enhance learning outcomes when compared to traditional educational approaches within the science domain, (Rutten, van Joolingen, & van der Veen, 2012). Simultaneously, a multitude of studies have demonstrated the efficacy of using self-explanation as a learning strategy to support the attainment of learning outcomes (Roy & Chi, 2005). Combining both instructional approaches should enable the design and development of cognitively interactive educational tools that effectively drive the attainment of learning goals both within and beyond the domain of science-focused education.

Active learning engages students during instruction in a meaningful manner by helping learners analyze, synthesize, evaluate, and integrate new information with existing information (Bonwell & Eison, 1991; Fiorella & Mayer, 2016). The iCAP (Interactive, Constructive, Active, Passive) Framework (Chi & Wylie, 2016) provides a conceptual model to support the utilization of instructional approaches that promote active learning. Four levels of activity are identified (going from low to high levels of engagement): (1) passive, (2) active, (3) constructive, and (4) interactive. The underlying premise for the framework holds that as an individual becomes more engaged during instruction, learning outcomes will increase. It would appear that computer-based simulations and the self-explanation strategy are an ideal fit within this framework for driving learner engagement, cognitive activity, and ultimately the attainment of learning goals.

Many studies demonstrate the efficacy of using self-explanation as a learning strategy to support knowledge and skill acquisition (Bielaczyc, Pirolli, & Brown, 1995; Chi, Leeuw, Chiu, & LaVancher, 1994; Chi, Bassok, Lewis, Reimann, & Glaser, 1989; McNamara, 2004; Renkl, Stark, Gruber, & Mandl, 1998). Further, the inclusion of (a) learner “training” on how to use the strategy (Bielaczyc et al., 1995), and (b) prompts to self-explain, drive application of the strategy (Chi et al., 1994) and significantly impact learning outcomes in a positive manner. However, learning outcomes may differ because of varying levels of learner application of the self-explanation strategy (Renkl, 1997; Roy & Chi, 2005).

The type of self-explanation prompt presented to learners provides some explanation for the variability in application of the strategy. Self-explanation prompts can be categorized into two major groups: (1) structured (closed) prompts; and (2) unstructured (open) prompts (Wylie & Chi, 2014). Structured prompts focus learner attention on specific information related to the content. An example might be a prompt followed by four possible explanations. The learner then selects an explanation that is most aligned with the prompt. Unstructured prompts differ from structured prompts in that learner support is limited or non-existent. Instead, the learner must generate a self-explanation without any assistance. This study investigates whether the type of self-explanation prompt presented influences application of the strategy, and ultimately learning outcomes.

Cognitive Load Theory (CLT) may provide some explanation for the variability in application of the self-explanation learning strategy. Two types of cognitive load are identified: (1) extraneous (i.e., the level of difficulty generated by the presentation of subject matter); and

(2) intrinsic (i.e., the inherent difficulty of the subject matter). Higher levels of extraneous cognitive load reduce working memory capacity and negatively impact the processing capabilities available to attend to the intrinsic complexities of the subject matter (Sweller, Ayres, & Kalyuga, 2011). The study that is the focus of this dissertation investigated if the type of self-explanation prompt presented affected the cognitive load placed on a learner.

Similarly, learner self-efficacy drives self-regulatory behaviors, i.e., the self-evaluation of learning progress, and is closely linked to the attainment of learning goals (Schunk, 1990; Zimmerman, 1990). When an individual perceives success during the learning process she is more likely to behave in a manner that supports the attainment of learning outcomes (Zimmerman, 1990). This study investigated if the self-explanation learning strategy affected learner self-efficacy.

To further explore the iCAP Framework, this study investigated if the overt generation of self-explanations (i.e., selecting explanations from a range of onscreen options or typing explanations in an onscreen text entry box) affected learning outcomes when compared to the non-overt (i.e., internal non-observable) generation of self-explanations. A true experimental pretest-posttest control group design was employed with participants randomly assigned to one of three treatments: (1) closed prompts - overt response; (2) open prompts – overt response, and (3) open prompts – non-overt response. Participants completed a self-paced simulation-based instructional module housed in an online platform (i.e., Blackboard) that included the following components: (1) pretest, (2) self-explanation tutorial, (3) fifteen discrete instructional activities, and (4) posttest. Self-reported measures of cognitive load and self-efficacy were captured. Learning outcomes were measured by calculating the difference between pretest and posttest scores for each treatment group.

Literature Review

This section provides a summary of the literature related to the following areas: (1) instructional simulations; (2) active learning and the iCAP framework; (3) measuring self-explanation; (4) self-explanation training and instructional prompts; (5) cognitive load and self-explanation; and (6) self-regulation, self-efficacy and self-explanation. The section concludes with an overview of the research questions that formed the focus of the study.

Instructional simulations

Instructional simulations provide learners with a context, environment, or activity that support the acquisition of information and the development of a mental model or schema that can be applied to support problem-solving and reasoning within a particular domain (Alessi & Trollip, 2001). Further, learning via simulations allows learners to explore realistic and hypothetical situations, without the stress or risk associated with a real-life environment (Van Berkum & De Jong, 1991). Simulations are often used to teach principles, where learners explore causal relationships to create a meaningful understanding of the principle represented in the simulation (Reigeluth, 1989). A variety of studies have demonstrated that simulation-based instruction can support the attainment of learning goals in a variety of contexts (Bangert-Drowns, Kulik, & Kulik, 1985; Kulik & Kulik, 1991).

However, it has been argued that the unstructured nature of an instructional simulation, particularly in terms of the lack of instructional guidance or support embedded in the simulation, can inhibit the effectiveness of this approach (Reigeluth & Schwartz, 1989). Further, the complex nature of the cognitive activities engaged in during a simulation (i.e., the development and testing of hypotheses, the identification of appropriate conclusions, and the activation of self-regulatory processes) may increase the cognitive demands placed on a learner (De Jong & Van Joolingen, 1998; Sweller et al., 2011; Tuovinen & Sweller, 1999).

In order to support the attainment of learning goals and maximize the effectiveness of an instructional simulation, a guided discovery method is recommended. During guided discovery learning, learners are provided with prompts and feedback throughout the instructional process. A meta-analysis of the literature related to this approach reveals that instructional simulations with embedded learner supports lead to improved learning when compared with other methods across a variety of domains (Alfieri, Brooks, Aldrich, & Tenenbaum, 2011).

Active learning and the iCAP framework

The term "learner engagement" appears ubiquitously in practice areas across the educational spectrum. A review of the academic literature related to the topic identifies behaviors that specifically define learner engagement into two primary areas: (1) motivation, and (2) cognitive engagement (Chi & Wylie, 2014). The former considers the precursor attitudes or interest level of an individual that motivate learning activity (Blumenfeld, Kempler, & Krajcik, 2006; Pintrich & De Groot, 1990; Zimmerman, 1990). The latter focuses on the cognitive activities (i.e., summarizing, self-explaining, etc.) that enable learners to acquire a meaningful comprehension within a domain (Chi & Wylie, 2014). For the purposes of this study, learner engagement centered on cognitive activities, and more specifically on the self-explanation learning strategy.

Active learning, a synonym for cognitive engagement, drives learners to process new information and integrate it with existing information to support the acquisition of knowledge or skills. The iCAP Framework (Chi, 2009; Chi & Wylie, 2014) identifies four types of learner engagement that can be used to design meaningful instructional activity. More specifically, the framework categorizes these activities into the following types: (1) interactive, (2) constructive, (3) active, and (4) passive. When organized into a taxonomy using this categorization, interactive activities involve the highest level of activity and learner engagement, whereas, passive activities involve the lowest level of activity and learner engagement (see Table 1). A description of each category utilizing iCAP specific examples follows.

Table 1 Taxonomy of Activities Using iCAP Framework (Wylie & Chi, 2014)

Level of Engagement	Activity Type	Activity
High Engagement	Interactive	Debating, Discussing
	Constructive	Self-explaining, Summarizing
	Active	Underlining, Repeating
Low Engagement	Passive	Reading, Listening

Passive engagement involves a learner receiving information by listening or viewing instructional materials or observing a facilitator without any further activity related to learning. Examples include: listening to an instructional podcast, viewing a learning video, and reading a textbook.

Active engagement involves a learner performing a mechanical or physical action that is related to the instructional content. Examples include: transcribing the narrative from an instructional podcast, rewinding and repeat watching specific elements of a learning video, and underlining sentences while reading a text-book.

Constructive engagement involves a learner generating or producing outputs beyond those that are provided in the instructional content. Examples include: reflecting on the information presented in an instructional podcast that integrates prior knowledge with new information, making a connection between related learning videos to generate a deeper understanding of the relationships between the content areas, and summarizing the elements of a text-book by generating new content.

Interactive engagement involves the learner collaborating with a peer or system in a manner that generates or constructs new and relevant content that reflects a deep understanding of the domain. Examples include: debating the content of an instructional podcast with a peer group to defend or deconstruct a position, participating in an online discussion forum related to a learning video to deliberate the merits of creating new content, and asking and answering questions with a small study group regarding a textbook.

There are a number of assumptions upon which the iCAP Framework is grounded. One of these assumptions holds that the overt (i.e., external) demonstration of learner activity supports the attainment of greater learning outcomes when compared to non-overt (i.e., internal) activity. This assumption is defended using the following arguments (Chi & Wylie, 2014): (1) overt activity can be monitored, analyzed, and verified for accuracy and intent; (2) cognitive activity that exerts a significant load on the learner can be reduced by externalizing outputs (i.e., when generating a summary of a specific text, it may be easier to write or type text as opposed to organizing and retaining the newly constructed information internally); and (3) external outputs enable a learner to easily refer to this material, infer new knowledge, and analyze the information to ensure proper comprehension.

This study investigated the assumption that overt constructive activity (i.e., self-explanation) supports the attainment of greater learning outcomes when compared to non-overt constructive activity (i.e., self-explanation).

Measuring self-explanation

There are two commonly accepted measures used to evaluate the efficacy of self-explanation: (1) quantity, and (2) quality (Roy & Chi, 2005). Quantity refers to the duration of time spent by learners developing self-explanations, and the number of individual self-explanations developed (Chi et al., 1994; Chi et al., 1989; Renkl et al., 1998). Learners that devote more time to generating self-explanations or develop greater quantities (i.e., numerically) of self-explanations, attain greater learning outcomes when compared to those who spend less time applying the strategy or developing fewer self-explanations (Wylie & Chi, 2014).

Similarly, in terms of quality, there are two categories of self-explanation: (1) high-quality, and (2) low-quality. High-quality self-explanations involve the integration of new information with existing information by the learner. Common forms include inferences (i.e., anticipative-reasoning), underlying principles (i.e., principle-based), and the identification of causal relationships (i.e., goal-operator explanations) (Renkl et al., 1998). Alternatively, low-quality self-explanations are less sophisticated and take the form of paraphrasing, repetition, and the simplistic analysis of content (Roy & Chi, 2005). Learners that generate higher-quality self-explanations attain greater learning outcomes when compared to learners that generate lower-quality self-explanations (Chi et al., 1994).

Self-explanation training and instructional prompts

Two types of instructional intervention successfully promote the use of self-explanation: (1) training learners to use the strategy, and (2) prompting learners to self-explain during instruction. Training learners to self-explain increases application, drives the effective use of the strategy (i.e., the generation of high-quality self-explanations), and supports the attainment of learning goals (Bielaczyc et al., 1995; Wong, Lawson, & Keeves, 2002).

Similarly, the provision of instructional prompts to self-explain drives application of the learning strategy and results in greater learning outcomes (Chi et al., 1994). Self-explanation prompts have been categorized into five specific types (Wylie & Chi, 2014): (1) menu-based, (2) resource-based, (3) scaffolded, (4) focused, and (5) open-ended. Unstructured prompts (i.e., open) (e.g., “Can you explain that?” or “What do you mean?”) promote the generation of self-explanations of varying quality (Chi et al., 1994). Structured (i.e., closed) prompts promote the generation of higher-quality self-explanations (O'Reilly, Symons, & MacLatchy-Gaudet, 1998; Renkl et al., 1998). A graphical representation presenting the prompt type and associated level of structure follows (see Table 2).

Table 2 Typology of Self-Explanation Prompts and Level of Structure (Wylie & Chi, 2014).

Self-explanation Type	Level of Structure
	Unstructured
Open-ended	
Focused	
Scaffolded	
Resource-based	
Menu-based	
	Structured

Menu-based and resource-based prompts (i.e., structured) are most commonly used in computer-based instructional environments (Wylie & Chi, 2014). A review of the literature suggests that closed prompts are more effective than open prompts when used within a computer-based instructional context (Berthold, Eysink, & Renkl, 2009; Butcher & Aleven, 2008; Gadgil, Nokes-Malach, & Chi, 2012; Johnson & Mayer, 2010; Kwon, Kumalasari, & Howland, 2011; Van der Meij & de Jong, 2011; Wylie & Chi, 2014). However, the existing literature provides no clear explanation as to why the structure of the prompt effects the efficacy of the self-explanation learning strategy in this computer-based instructional context. This study investigated how the structure of a self-explanation prompt might impact application of the self-explanation learning strategy, and ultimately learning outcomes, by asking if learners presented with closed prompts during an instructional simulation will achieve greater learning outcomes when compared to learners presented with open prompts.

Cognitive load and self-explanation

Cognitive Load Theory (CLT) holds that the cognitive demands placed on a learner during instruction directly impact the working memory resources available to process information (Sweller et al., 2011). Two types of cognitive load are identified: (1) intrinsic, and (2) extraneous. Intrinsic load refers to the complexity of the subject matter (i.e., how difficult a specific knowledge domain is to comprehend). Extraneous load refers to the demands placed on the learner by external entities such as instructional materials, or the learning strategies presented.

CLT identifies two types of working memory resource (Sweller et al., 2011): (1) germane, and (2) extraneous. Germane resources support cognitive processes used to comprehend the inherent complexity of the subject matter. Extraneous resources support the cognitive processes used during instruction (i.e., comprehending instructional materials; completing instructional activities; and utilizing instructional strategies).

Self-explanation is a cognitively demanding activity and learner reluctance to employ the strategy is frequently observed (Renkl, 1997). As previously mentioned, prompt type appears to have an effect on application of the learning strategy and learning outcomes. However, a review of the literature provides no clear explanation on whether the type of prompt (i.e., closed vs. open) impacts the cognitive load placed on a learner, and application of the learning strategy. Ultimately this could impact learning outcomes. This study investigated the relationship between prompt type, cognitive load, and application of the learning strategy, by asking if closed prompts place lower levels of cognitive load on a learner when compared to open prompts.

Self-regulation, self-efficacy, and self-explanation

Self-regulation refers to a set of self-directed processes by which learners manage emotions, thoughts, behaviors, and actions to support the attainment of learning goals (Zimmerman, 2002). A learner engages in self-regulation by being metacognitively, motivationally, emotionally, and behaviorally active in the learning process (Zimmerman, 1989). Examples of self-regulatory activity include: (1) self-observation (i.e., a learner evaluates behaviors and quality or progress of their work), (2) self-judgment (i.e., a learner compares performance with identified goals), and (3) self-reaction (i.e., a learner evaluates performance and determines satisfaction level) (Schunk, 1990).

Self-efficacy refers to the belief or confidence an individual holds in their ability to attain goals (Bandura, 1997). Self-efficacy drives self-regulatory behaviors (i.e., the evaluation of learning progress, that are closely linked to the attainment of learning goals) (Schunk, 1990; Zimmerman, 1990). Further, when an individual perceives success during the learning process they are more likely to behave in a manner that supports the attainment of learning outcomes (Zimmerman, 1990). Clearly, self-efficacy and self-regulation are important constructs to consider when evaluating learning strategies such as self-explanation.

A review of the related literature provides no clear description of the relationship between learner self-efficacy and application of the self-explanation learning strategy. More specifically, gaps in our understanding exist in how the confidence level a learner holds in his/her comprehension of a particular domain may be affected by application of the self-explanation learning strategy. Therefore, this study asked, what effect if any, does the self-explanation learning strategy have on learner self-efficacy?

Research Questions

In summary, based on a review of literature related to self-explanation and computer-based instructional simulations, this study investigated the following research questions:

1. During an instructional simulation, what effect do closed and open self-explanation prompts have on learning outcomes, application of the self-explanation strategy, and cognitive load?
2. During an instructional simulation, what effect does overt and non-overt learner activity have on learning outcomes?
3. During an instructional simulation, what effect does the self-explanation learning strategy have on learner self-efficacy?

CHAPTER II

METHOD

This section describes the research methods used for the study. The following are presented and explained: (1) participant group, (2) experimental design, (3) experimental treatments, (4) instructional materials, (5) measures and instruments, and (6) experimental procedure and data collection.

Participants

A review of the literature in the area indicates a wide variance in sample sizes used in experiments related to the self-explanation learning strategy, for example: 54 (Mayer, Dow, & Mayer, 2003), 36 (Renkl et al., 1998), 24 (Bielaczyc et al., 1995), 14 (Chi et al., 1994), and 6 (Neuman & Schwarz, 2000).

Participants in the study were 67 actively registered undergraduate students in a computer literacy course during the fall semester of 2017 and the spring semester of 2018, at a major Mid-Atlantic university in the United States of America. The course was selected because it provided access to a diverse student group in an effort to ensure the heterogeneity of the study population. An announcement requesting participation was presented to this student group in coordination with course instructors. Students were offered extra credit towards their final grade in the course as an incentive for participation.

A demographic survey of participants captured information related to (1) grade point average (GPA), (2) major, and (3) academic level. The grade point average (GPA) for all participants in the study was 2.93 (see Table 3).

Table 3 Participant Grade Point Average (GPA) by Treatment

Treatment	GPA
Control	2.84
CP	2.85
OP	3.11
Mean GPA	2.93

Participants in the study were split across multiple declared majors (see Table 4).

Table 4 Participant Major by Treatment

Major	NO	CP	OP
Business	11	3	6
Communications	9	8	10
Criminal justice	6	3	5
Health & Human Services	3	3	1
Undeclared			1

Participants in the study were split across multiple undergraduate academic levels (see Table 5).

Table 5 Participant Academic Level by Treatment

	NO	CP	OP
Freshman	11	3	6
Sophomore	9	8	10
Junior	6	3	5
Senior	3	3	1
Other			1

Experimental Design

A true experimental pretest-posttest control group design was employed during the study with participants randomly assigned to each treatment. The independent variables were: (1) structured prompts (i.e., closed prompts) and overt explanations; (2) unstructured prompts (i.e., open prompts) and overt explanations; and (3) unstructured prompts (i.e., open prompts) and non-overt explanations (i.e., control). The dependent variables were: (1) learning outcomes (i.e., the difference between performance scores on a pretest and posttest), (2) application of the self-explanation learning strategy (i.e., the time spent generating self-explanations, quantity of self-explanations, quality of self-explanations, and accuracy of self-explanations), (3) cognitive load (i.e., the extraneous and intrinsic load as reported by participants), and (4) self-efficacy (i.e., the perceived knowledge level, and confidence in this knowledge level, related to the domain). A graphic outlining the research model and relationships between these variables is presented in Figure 1.

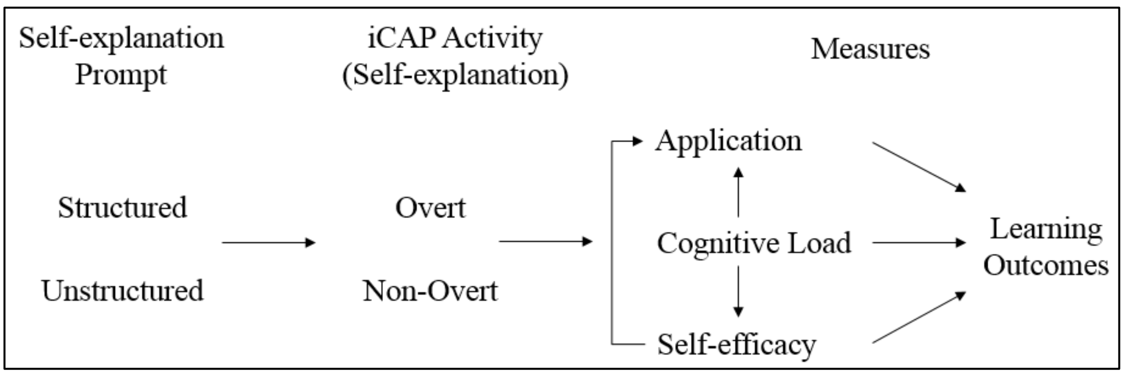

Figure 1. Research model.

A pretest-posttest control group design requires that all conditions are the same for the control group and experimental groups. However, each experimental group is exposed to a unique or particular treatment, while the control group is not (Dimitrov & Rumrill Jr, 2003). In this study, the unique treatments were the type of prompt (i.e., closed or open) and the response activity (i.e., overt or non-overt). Participants were randomly assigned to each of the groups thus controlling for regression and selection factors that may otherwise impact the make-up of the experimental groups (Gay, Mills, & Airasian, 2011).

A review of the literature suggests that maturation and history pose challenges to the internal validity of an experiment when utilizing this statistical design if participants are exposed to a treatment for long periods of time (Dimitrov & Rumrill Jr, 2003; Gay et al., 2011). However, neither threat is considered to be significant for this experiment because the duration of the study was no longer than one hour. The possibility of a pretest-posttest interaction, whereby information included in the questions used in each assessment may have influenced test performance, was considered to be a significant threat to the external validity of the experiment. To counteract this risk, assessment (i.e., pretest/posttest) and instructional materials included variable surface features to avoid repetition of questions or activities (Dimitrov & Rumrill Jr, 2003; Gay et al., 2011).

Experimental Treatments

The purpose of this study was to: (1) measure the effect different types of self-explanation prompt have on application of the self-explanation strategy, learning outcomes, and cognitive load during an instructional simulation; (2) measure the effect overt and non-overt self-explanation activity has on learning outcomes; and (3) measure the effect the self-explanation learning strategy has on learner self-efficacy. Three experimental treatments were used in this study: (1) structured prompts & overt explanations, (2) unstructured prompts & overt explanations, and (3) unstructured prompts & non-overt explanations. A description of the response type and prompt type treatment conditions follows. Examples of each prompt type are presented in Appendix A.

Prompt type

Controlling prompts by type enabled the researcher to test the effect each treatment had on learning outcomes, application of the learning strategy, cognitive load, and self-efficacy. A description of each prompt type follows:

Structured self-explanation prompts (i.e., closed prompts) were presented as menu-based prompts throughout the instructional module. After being presented with an instructional activity containing a closed prompt, participants overtly generated a self-explanation by selecting a statement from a list of possible explanations.

Unstructured self-explanation prompts (i.e., open prompts) were presented as text-entry fields throughout the instructional module. After being presented with an instructional activity containing a structured self-explanation prompt, participants overtly generated a self-explanation by typing in an onscreen field.

Activity type

Controlling response types enabled the researcher to test one of the assumptions underlying the iCAP framework (i.e., overt activity results in greater learning outcomes when compared to non-overt activity). Therefore, three treatments were divided across two types of activity: (1) overt self-explanation activity, and (2) non-overt self-explanation activity.

Overt self-explanation activity required participants to generate self-explanation prompts in a visible manner that allowed for learner activity to be recorded. Non-overt self-explanation activity did not require participants to generate self-explanations in a visible manner. A treatment group measuring non-overt structured prompts was not included in the study because the very act of selecting a response to a menu-based self-explanation is an overt act in and of itself.

Instructional Materials

In addition to the unique self-explanation prompts presented to learners during the instructional module, the following instructional materials were shared with all treatments:

Self-explanation tutorial: A self-paced online tutorial training participants on how to use the self-explanation strategy. This was completed prior to beginning the instructional module (see Appendix B). The purpose of this tutorial was to ensure that all participants received standardized training on how to effectively utilize the self-explanation learning strategy.

Computer-based simulation: The computer-based simulation used in the study was designed and developed by the PhET Project at the University of Colorado, Boulder (see Appendix C). The PhET project develops interactive math and science simulations that can be integrated into instructional modules utilizing a guided learning model. In this study, the simulation was focused on acquiring knowledge of formulae used to calculate the mass, volume, and density of an object when placed in a pool of water.

The scenario presented via the simulation included four cubes of varying mass, volume, and density. These cubes were positioned alongside a pool of water. When each object was placed in the water different outcomes were presented (i.e., an object might either float or sink). The underlying mathematical model was not evident to learners, however, by selecting from a range of options presented onscreen, different information was displayed (i.e., the mass, volume, or density of the objects). Utilizing this information in association with other onscreen direction, learners were guided to deduce the formula used to calculate the mass, volume, or density of the objects.

Instructional module: The focus of the instructional module used in the experiment was on learning how to calculate the (1) mass, (2) volume, and (3) density of an object, by placing it in water. The design of the instructional module was consistent with the guided discovery learning approach (Alfieri et al., 2011). Using this approach, learners were provided with a set of structured activities that were completed while using an instructional computer-based simulation. Four learning objectives were the focus of the instructional module (see List 1).

List 1 Instructional Module Learning Objectives

At the end of this instructional module participants will be able to calculate the:

1) volume of an object when using the water displacement method
2) volume of an object when given the mass and density of the object
3) mass of an object when given the volume and density of the object
4) density of an object when given the mass and volume of the object

A set of fifteen activities were presented during the instructional module. Objective one (see List 1) had two specific activities, objectives two, three, and four each had four specific activities. The structure of the instructional module and the content focus of each of the instructional activities was standardized across all treatments. The prompt type and response type varied by experimental treatment. A record of these individual activities is presented in Appendix D.

Measures and Instruments

Learning outcomes, self-explanation application, cognitive load, and self-efficacy were dependent variables measured in this study. A description of each measure and the associated instruments follow. A summary is presented afterwards (see Table 6).

Learning outcomes: Three measures were used to assess learning outcomes within this study: (1) performance on a pretest assessment, (2) performance on a posttest assessment, and (3) the difference between scores on both tests. The difference in performance on each assessment is considered to be the learning outcome (Dimitrov & Rumrill Jr, 2003). Each assessment contained fifteen (15) multiple choice questions. No partial credit was available. A table of specifications for each assessment can be found in Appendix E. Individual pretest items can be found in Appendix F. Individual posttest items can be found in Appendix G.

The pretest and posttest were evaluated for reliability using the Kuder-Richardson Formula 20 (KR-20) test. This test checks for the internal consistency of assessments with dichotomous choices (Kuder & Richardson, 1937). Values are reported on a range from zero (0) to one (1). A high value indicates reliability. The KR-20 value for the pretest was 0.77, and the KR-20 value for the posttest was 0.91. Both measures confirm the reliability of the instrument.

Application of self-explanation strategy: Four measures were used to assess application of the self-explanation learning strategy: (1) time spent generating self-explanations (i.e., the time taken to complete the instructional module); (2) quantity of self-explanations generated; (3) quantity of high-quality self-explanations generated; and (4) accuracy of self-explanations.

Cognitive load: Two measures were used to assess cognitive load: (1) intrinsic cognitive load (i.e., the level of complexity the learner associated with the domain), and (2) extraneous cognitive load (i.e., the mental effort required to self-explain).

Learner self-efficacy: Two measures were used to assess learner self-efficacy: (1) perceived knowledge level within the domain, and (2) confidence level related to knowledge within the domain. Both of these measures were captured immediately before and immediately after the instructional module.

Table 6 Research Questions, Measures, and Instruments

Research Focus	Research Question	Measure	Instrument
Prompt Type	What effect do structured and unstructured prompts have on learning outcomes during an instructional simulation?	• Average pretest and posttest scores • Difference between average pretest and posttest scores	Pretest & Posttest Assessment • 3 declarative knowledge questions 12 problem-solving questions
	What effect do structured and unstructured prompts have on application of the self-explanation learning strategy during an instructional simulation?	• Average time spent generating self-explanations • Average quantity of self-explanations generated • Average quantity of high-quality self-explanations generated • Average quantity of accurate self-explanations generated	
	What effect do structured and unstructured prompts have on the cognitive load placed on a learner during an instructional simulation?	• Average cognitive load (intrinsic and extraneous) after completing instructional module	• 9-point cognitive load scale

Research Focus	Research Question	Measure	Instrument
Activity Type	What effect does overt and non-overt activity have on structured and unstructured prompts have on learning outcomes?	• Average pretest and posttest scores • Difference between average pretest and posttest scores	Pretest & Posttest Assessment • 3 declarative knowledge questions 12 problem solving questions
Self-efficacy	What effect does the self-explanation learning strategy have on self-efficacy?	• Two measures for self-efficacy (knowledge level and confidence) • Average self-efficacy measures taken pre and post instructional module • Difference between average pre and post instructional module scores	• 9-point scale

Experimental Procedure and Data Collection

At the beginning of the 2017 fall semester, instructors teaching a computer literacy class at a major Mid-Atlantic university were contacted requesting permission to invite students enrolled in their classes to participate in this study. Two instructors agreed to participate. Both instructors taught multiple sections of this course in both face-to-face and online contexts.

A complete list of students enrolled in each class section was provided to the researcher. An invitation to participate in the study was distributed via email by the instructors to all students in these classes. Extra credit was offered to any students that completed the study in an effort to incentivize participation. Once students agreed to participate, they were randomly assigned to one of three treatments. Directions on how to access the study modules on the Blackboard learning management system were also distributed to the students in these classes.

Participants began the experiment by completing an online informed consent form (see Appendix H). This was followed by a fifteen question knowledge assessment (i.e., pretest) that had a 15-minute time limit for completion. The test items and time limit were standardized across all treatments.

Next participants were presented with an online tutorial focused on: (1) the self-explanation learning strategy; (2) foundational definitions related to mass, volume, and density; and (3) directions on how to use the instructional simulation. The content presented in this tutorial was standardized across all treatments and took approximately 10 minutes to complete.

Next, participants completed a demographic survey and a set of three practice activities. The demographic survey captured data related to (1) participant GPA, (2) academic level, and (3) domain area of majors. The practice activities supported application of the self-explanation learning strategy and using the simulation. The survey questions and practice activities were standardized across each experimental treatment (see Appendix I). However, the structure of the prompts presented varied according to treatment (see Appendix J).

Upon completion of the survey and practice activities, participants began the instructional module. At the beginning of the instructional module, participants were asked two questions related to the self-efficacy measure (see Appendix K): (1) How would you rate your level of knowledge within the subject area? and (2) How confident are you in the level of knowledge you have in the subject area? The scale for both of these measures ranged from 1 (very, very low) to 9 (very, very high). These questions were standardized across all treatments.

Next, participants completed a set of fifteen instructional activities that required use of the instructional simulation. The structure of the instructional module and the content focus of each of the instructional activities was standardized across all treatments. However, the prompt type and response type varied by experimental treatment.

The closed-prompts treatment group received menu-based prompts that required overt activity. The open-prompts treatment group received text entry prompts that required overt activity. The non-overt treatment group received open prompts that required non-overt activity. Participants in this group were asked to record if they had generated a self-explanation by answering a question (i.e., Did you generate a self-explanation? Yes/No). A list and description of these individual activities are presented in Appendix D.

After completing the fifteen instructional activities participants completed a manipulation check to ensure they were only exposed to one experimental treatment (see Appendix L). Next participants self-reported two measures for cognitive load (intrinsic and extraneous) experienced during the simulation (see Appendix M). The scale for both of these measures ranged from 1 (very, very low) to 9 (very, very high). These questions were standardized across all treatments.

Finally, participants reported two measures related to self-efficacy upon completing the instructional module (see Appendix K). Again participants were asked: (1) How would you rate your level of knowledge within the subject area? And (2) How confident are you in the level of knowledge you have in the subject area? The scale for both of these measures also ranged from 1 (very, very low) to 9 (very, very high). These questions were standardized across all treatments.

Upon completion of the instructional module, participants completed a fifteen question knowledge assessment (i.e., posttest) that had a 15-minute time limit for completion. The test items and time limit were standardized across all treatments (see Appendix G). After this assessment, participants were advised that they had completed the study.

Throughout the experiment, a ruse was employed to motivate performance. The ruse told participants that they would receive bonus credit for achieving a score of 80% or higher on the posttest assessment. When the study window closed, an email message was sent to all participants that completed the study that informed them of the ruse, and that each participant in the study received the full total of extra credit points available. A graphical representation of the study procedure is presented in Appendix N.

CHAPTER III

FINDINGS

This study investigated three primary research questions:

1. During an instructional simulation, what effect do closed and open self-explanation prompts have on learning outcomes, application of the self-explanation learning strategy, and cognitive load?
2. During an instructional simulation, what effect does overt and non-overt learner activity have on learning outcomes?
3. During an instructional simulation, what effect does self-explanation have on learner self-efficacy?

An analysis of each question, supported by data, is presented in this chapter.

Prompt Type

In this section, an analysis of results pertaining to the effects different types of self-explanation prompt (i.e., closed/open) have on learning outcomes, application of the learning strategy, and cognitive load is presented. Each measure is presented separately and begins with a report on the related descriptive statistics.

Learning outcomes

Learning outcomes were defined as the difference between the scores attained on a pretest completed prior to the instructional module and a posttest completed after the instructional module. Throughout this analysis, the difference in posttest and pretest score is presented as a gain score (Dimitrov & Rumrill Jr, 2003). The gain score is calculated by subtracting the pretest score from the posttest score. The range for the gain scores is -15 to + 15.

Descriptive analysis – learning outcomes.

Measures related to pretest scores were captured for all treatments (see Table 7).

Table 7 Descriptive Statistics for Pretest Score

Treatment	N	Min	Max	Mean	Std. Dev.	Median	Skewness	Kurtosis
All Combined	67	0	15	9.21	3.715	8	-0.099	-0.299
Control	29	2	15	9.66	3.508	9	0.058	-0.744
Closed	17	0	15	8.65	3.807	8	-0.339	0.308
Open	21	0	15	9.05	4.018	8	-0.030	-0.157

Measures related to posttest scores were captured for all treatments (see Table 8).

Table 8 Descriptive Statistics for Posttest Score

Treatment	N	Min	Max	Mean	Std. Dev.	Median	Skewness	Kurtosis
All Combined	67	1	15	10.55	4.550	13	-0.446	-1.453
Control	29	1	15	10.07	5.007	13	-0.310	-1.654
Closed	17	6	15	11.71	3.531	14	-0.516	-1.488
Open	21	3	15	10.29	4.660	13	-0.384	-1.818

Measures related to the gain score (i.e., difference in scores) were calculated for all treatments (see Table 9).

Table 9 Descriptive Statistics for Difference Between Tests

Treatment	N	Min	Max	Mean	Std. Dev.	Median	Skewness	Kurtosis
All Combined	67	-14.0	12.0	1.34	4.194	1.0	-0.522	2.053
Control	29	-14.0	8.0	0.41	4.371	1.0	-1.141	3.202
Closed	17	-2.0	10.0	3.06	2.861	3.0	0.659	0.919
Open	21	-6.0	12.0	1.24	4.582	0.0	0.396	0.131

A visual inspection of the data using histograms (see Appendix O) suggested that data may not be normally distributed. Further, a review of the data in relation to skewness and kurtosis revealed that many of the values were not close to zero (Tables 6-8). This indicated the data might not be normally distributed. In order to gain statistical evidence, Kolmogorov-

Smirnov and Shapiro-Wilk tests were completed. The results of these tests confirmed the assumption that the majority of data was not normally distributed (see Appendix P). Accordingly, all data needed to be analyzed using non-parametric methods. In order to perform the equivalent of a repeated measure analysis of variance (ANOVA) amongst three treatment groups, a combination of a between-groups and within-group analyses was applied.

Between-groups analysis – learning outcomes.

In order to perform a between-groups analysis, a gain score was calculated. Then, a Kruskal-Wallis test, the non-parametric equivalent of an ANOVA test, was performed. A mean rank is calculated when reporting this test. This indicated that there was no statistical difference in learning outcomes between treatment groups ($\chi^2(2) = 5.147$, $p = 0.076$), with a mean rank of 30.36 for the control treatment, a mean rank of 43.15 for the closed-prompts treatment, and a mean rank of 31.62 for the open-prompts treatment. Results of the analysis are presented in Table 10.

Table 10 Mean Rank of Test Gain Scores by Treatment

Treatment	N	Mean Rank
Control	29	30.36
Closed	17	43.15
Open	21	31.62

Within-group analysis – learning outcomes.

In order to understand the within-group differences between pretest and posttest scores separately for each group, three Wilcoxon signed-rank tests, the non-parametric equivalent of a dependent t-test (or repeated measures ANOVA) were performed. The Wilcoxon signed-rank test indicated that the difference between the pretest and posttest scores for the closed-prompts treatment (*Mdn=3.0,* Z= -3.218, $p < 0.000$) was statistically significant. Differences between pretest and posttest scores for the control (*Mdn=1.0*, Z= -0.988, $p < 0.332$) and open-prompts treatment (*Mdn=0.0*, Z= -1.169, $p < 0.243$) were not significantly different. The effect size for the closed-prompts treatment was medium (-0.78) (Cohen, 1992). (Cohen suggested that d=0.2 be considered a 'small' effect size, 0.5 represents a 'medium' effect size and 0.8 a 'large' effect size.). Results are presented in Table 11.

Table 11 Difference Between Pretest and Posttest Scores by Treatment

Treatment	Z	N	P	Effect size
Control	-0.988	29	0.332	-0.183
Closed	-3.218	17	0.000	-0.780
Open	-1.169	21	0.243	-0.255

Summary of findings – prompt structure and learning outcomes

Results of the study revealed that closed prompts more effectively drive learning outcomes when compared to open prompts. Participants in the closed-prompts treatment had the largest learning gain between pretest and posttest *(M=3.06)*. This was followed by the open-prompts treatment *(M=1.24)*. Finally, the control (i.e., non-overt) treatment had the smallest learning gain *(M=0.41)* (see Figure 2).

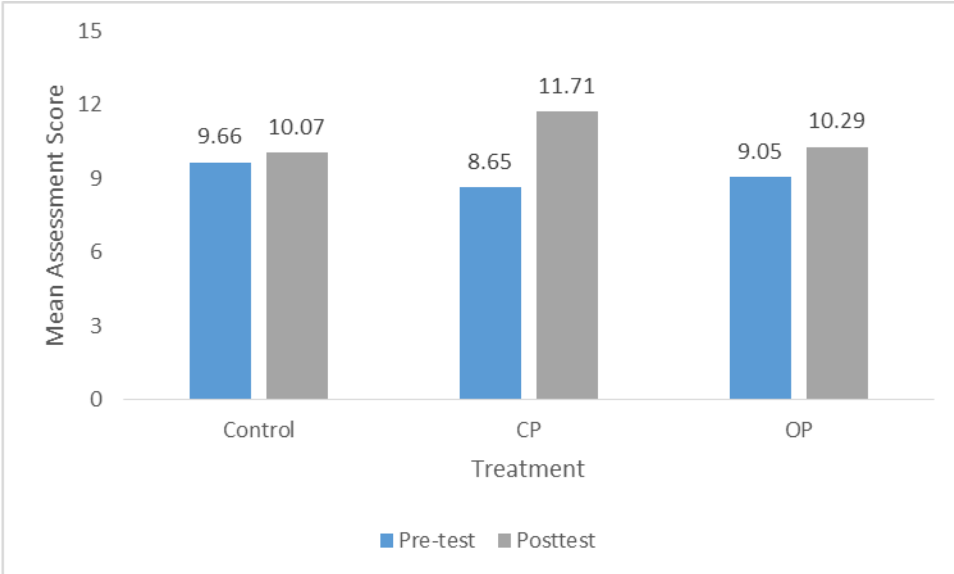

Figure 2. Mean learning gain by treatment.

A within-group analysis revealed that the learning gain (the difference between pretest and posttest scores) was significantly different for the closed-prompts treatment, however, the learning gain for the open prompts and control treatments (non-overt) were not significantly different *(CP: p = 0.000; OP: p = 0.243; NO: p = 0.332)*. Further, the effect size for the closed-prompts treatment was medium *(CP Effect Size-0.780)*. In order to understand the drivers of the comparatively more effective closed-prompts treatment, the analysis focused on measures related to application of the learning strategy.

Application of learning strategy

Application of the learning strategy focused on four measures captured while participants completed the instructional module: (1) time spent generating self-explanations, (2) quantity of self-explanations generated, (3) quantity of high-quality self-explanations generated, and (4) quantity of accurate self-explanations generated. In this section, the results for each of these measures are presented separately.

Descriptive analysis – application of learning strategy.

Measures related to the time spent completing the instructional module were captured for all treatments (see Table 12).

Table 12 Descriptive Statistics for Time Spent Completing the Instructional Module

	N	Min	Max	Mean	Std. Dev.	Median	Skewness	Kurtosis
All Combined	67	2.19	32.30	15.38	9.647	12.5	0.415	-1.207
Control	29	2.19	32.30	12.52	8.454	10.21	0.820	-0.234
Closed	17	2.43	26.26	10.30	6.512	9.37	0.898	0.611
Open	21	9.43	32.26	23.43	8.440	30.0	-0.696	-1.261

Measures related to the quantity of self-explanations generated during the instructional module were captured for all treatments (see Table 13).

Table 13 Descriptive Statistics for Quantity of Self-Explanations

	N	Min	Max	Mean	Std. Dev.	Median	Skewness	Kurtosis
All Combined	67	0	15	12.36	3.907	14	-1.787	2.876
Control	29	0	15	11.28	4.407	13	-1.344	1.294
Closed	17	15	15	15.00	0	15	0	0
Open	21	0	15	11.71	3.888	13	-1.641	2.991

Measures related to the quantity of high-quality self-explanations generated during the instructional module were captured for the closed prompts and open-prompts treatments only (see Table 14). The non-observable nature of activity in the control (i.e., non-overt) treatment meant that the quality of self-explanations was not captured.

Table 14 Descriptive Statistics for Quality of Self-Explanations

	N	Min	Max	Mean	Std. Dev.	Median	Skewness	Kurtosis
All Combined	38	0	13	5.39	4.097	5.0	0.297	-1.075
Control	NA							
Closed	17	2	13	7.53	3.466	7.0	0.196	-1.204
Open	21	0	11	3.67	3.799	3.0	0.817	-0.551

Measures related to the accuracy of self-explanations generated during the instructional module were captured for the closed prompts and open-prompts treatments only (see Table 15). The non-observable nature of activity in the control (i.e., non-overt) treatment meant that the accuracy of self-explanations was not captured.

Table 15 Descriptive Statistics for Accuracy of Self-Explanations

	N	Min	Max	Mean	Std. Dev.	Median	Skewness	Kurtosis
All Combined	38	0	14	6.55	4.183	6.0	0.268	-0.827
Control	NA							
Closed	17	3	14	8.29	3.933	8.0	0.296	-1.387
Open	21	0	13	5.14	3.915	6.0	0.373	-0.756

A visual inspection of the data using histograms (see Appendix O) suggested that data may not be normally distributed. Further, a review of the data in relation to skewness and kurtosis revealed that many of the values were not close to zero (see Table 15). This indicated the data might not be normally distributed. In order to gain statistical evidence, Kolmogorov-Smirnov and Shapiro-Wilk tests were completed. The results of these tests confirmed the assumption that the majority of data was not normally distributed (see Appendix P). Accordingly, all data were analyzed using non-parametric methods.

Time spent generating self-explanations.

Measures related to the time taken to complete the instructional module were automatically captured for each treatment using the Blackboard learning management system. A

Kruskal-Wallis test indicated that there was a statistically significant difference in the time spent generating self-explanations between treatments ($\chi^2(2) = 21.33$, $p < 0.05$), with a mean rank of 50.02 for the open-prompts treatment, a mean rank of 28.45 for the control treatment, and a mean rank of 23.68 for the closed-prompts treatment. Results of the analysis are presented in Table 16.

Table 16 Mean Rank of Time Spent Completing Instructional Module by Treatment

Treatment	N	Mean Rank
Control	29	28.45
Closed	17	23.68
Open	21	50.02

Post-hoc tests, conducted as Mann-Whitney tests (i.e., the non-parametric equivalent of independent t-tests), were performed to test for pairwise differences. A Mann-Whitney test indicated that there was a statistically significant difference between the time spent generating self-explanations by the open-prompts treatment *(Mdn=30.0)* when compared to the closed-prompts treatment *(Mdn=9.37), U=39, p < 0.000, r = -0.67*. Similarly, a Mann-Whitney test indicated that there was a statistically significant difference between the time spent generating self-explanations by the open-prompts treatment *(Mdn=30.0)* when compared to the control treatment *(Mdn=10.21), U=107.5, p < 0.000, r = -0.55*. Finally, A Mann-Whitney test indicated that there was not a statistically significant difference in the time spent generating self-explanations by the closed-prompts treatment *(Mdn=9.37)* when compared to the control treatment *(Mdn=10.21), U=210.5, p < 0.420, -0.12*. Results of the analysis are presented in Table 17. A Bonferroni correction of 0.05/3=0.0167 applies.

Table 17 Difference in Time Spent Completing Instructional Module

Treatment Comparison	U	Z	N	P	Effect size
Control vs Closed	210.5	-0.819	46	0.420	-0.12
Closed vs Open	39.0	-4.097	38	0.000	-0.67
Control vs Open	107.5	-3.873	50	0.000	-0.55

Summary of findings – prompt structure and quantity of time

Results of the study revealed that open prompts drive learners to spend more time generating self-explanations when compared to closed prompts (see Figure 3). Participants in the open-prompts treatment spent the largest amount of time completing the instructional module *(M=23:43 min)*. This was followed next by the control (i.e., non-overt) treatment *(M=12:52 min)*. Finally, the closed-prompts treatment spent the least amount of time *(M=10:30 min)*. Further, the open-prompts treatment spent significantly more time generating self-explanations when compared to the other two treatments (see Table 17).

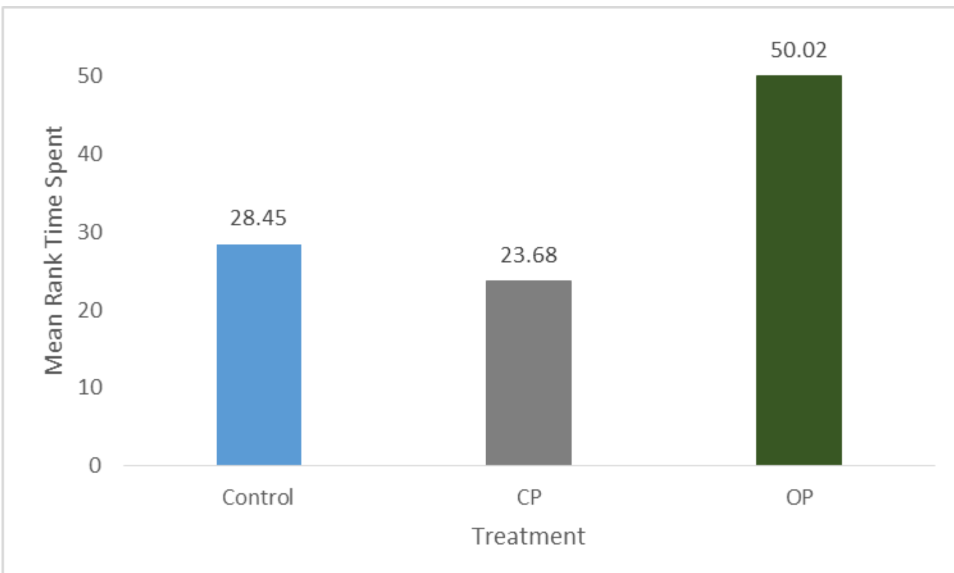

Figure 3. Mean rank time spent generating self-explanations.

An assumption is made that the time spent completing the instructional module closely correlates with the time spent generating self-explanations. This assumption is based on the fact that each individual activity presented during the instructional module centers on the generation of self-explanations. It is likely that the difference between the open-prompts treatment, and the closed-prompts and control treatments is caused by the extra time required to generate self-explanations in a typed format (Conati & Vanlehn, 2000). However, the increased time spent during the instructional module (i.e., applying the strategy) did not result in greater learning outcomes for the open-prompts treatment (see Figure 2). Further investigation is required to explain why the quantity of time spent generating self-explanations was not a factor that supported the attainment of greater learning outcomes for the open-prompts treatment. In the next section, an analysis of the quantity of self-explanations generated is presented.

Quantity of self-explanations generated

Measures related to the quantity of self-explanations generated while completing the instructional module were automatically captured using the Blackboard learning management system for all treatments. A Kruskal-Wallis test indicated that there was a significant difference in the quantity of self-explanations generated between treatments ($\chi^2(2) = 19.75$, $p < 0.05$), with a mean rank of 51.00 for the closed-prompts treatment, a mean rank of 28.26 for the open-prompts treatment, and a mean rank of 28.19 for the control treatment. Results of the analysis are presented in Table 18.

Table 18 Mean Rank of Total Number of Self-Explanations

Treatment	N	Mean Rank
Control	29	28.19
Closed	17	51.00
Open	21	28.26

Post-hoc tests, conducted as Mann-Whitney tests, were performed to test for pairwise differences. Tests indicated that there was a statistically significant difference in the quantity of self-explanations generated by the closed-prompts treatment *(Mdn=15.0)* when compared to the open-prompts treatment *(Mdn=13.0)*, $U=51$, $p < 0.000$, $r = -0.69$. Similarly, a Mann-Whitney test indicated that there was a statistically significant difference in the quantity of self-explanations generated by the closed-prompts treatment *(Mdn=15.0)* when compared to the control treatment *(Mdn=13.0), U=85, p < 0.000, r = -0.61*. Likewise, a Mann-Whitney test indicated that the quantity of self-explanations generated by the control treatment *(Mdn=13.0)* was statistically different from the open-prompts treatment *(Mdn=13.0), U=297.5, p = 0.004, r = -0.02*. However, in the case of the latter the effect size is very small. Results of the analysis are presented in Table 19.

Table 19 Difference in Quantity of Self-Explanations

Treatment Comparison	U	Z	N	P	Effect size
Control vs Closed	85.0	-4.118	46	0.000	-0.61
Closed vs Open	51.0	-4.246	38	0.000	-0.69
Control vs Open	297.5	-0.140	50	0.004	-0.02

Summary of findings – prompt structure and quantity of self-explanations

Results of the study revealed that closed prompts promote the generation of greater quantities of self-explanations when compared to open prompts (see Figure 4). Participants in the closed-prompts treatment developed the largest quantity of self-explanations *(M=15)*. This was followed next by the open-prompts treatment *(M=11.7)*. Lastly, the control (i.e., non-overt) treatment generated the least amount of self-explanations *(M=11.3)*. The closed-prompts treatment generated significantly more self-explanations when compared to both the open prompts and control treatments (see Table 18). In both cases the effect size was medium. The open-prompts treatment generated significantly more self-explanations when compared to the control treatment, however, in this case, the effect size is small (see Table 19).

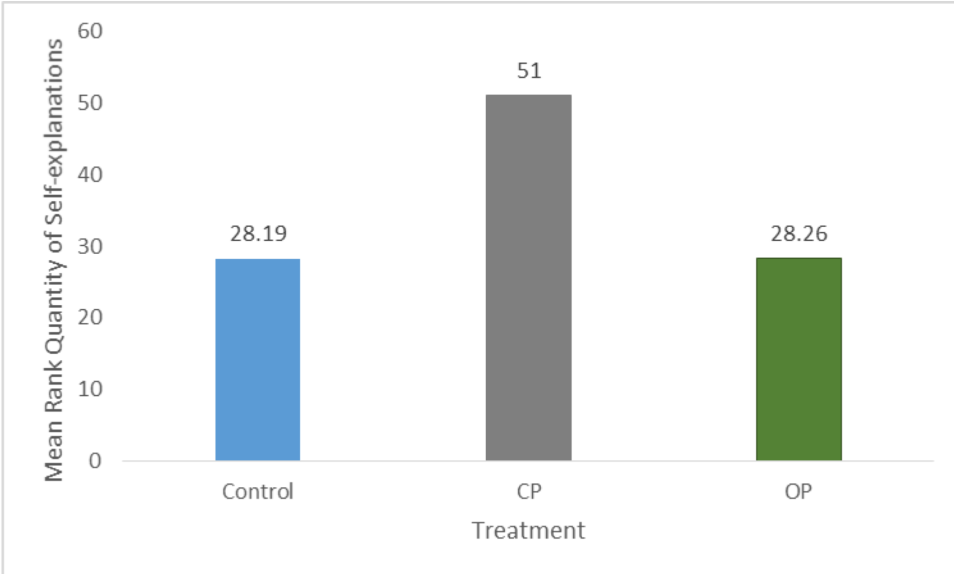

Figure 4. Mean rank quantity of self-explanations generated.

A further analysis looked at the quantity of self-explanations generated by participants as they progressed through the instructional module. This analysis tracked the number of completions for each of the fifteen instructional activities by individual participants in each treatment. A percentage completion rate was then calculated for each treatment.

Participants in the closed-prompts treatment had a completion rate of 100% for each activity. However, participants in the control (i.e., non-overt) and open-prompts treatments had varying levels of completion across all activities. Further, as the instructional module progressed there was an overall decline in completion rates for both the control (i.e., non-overt) and open-prompts treatments (see Figure 5).

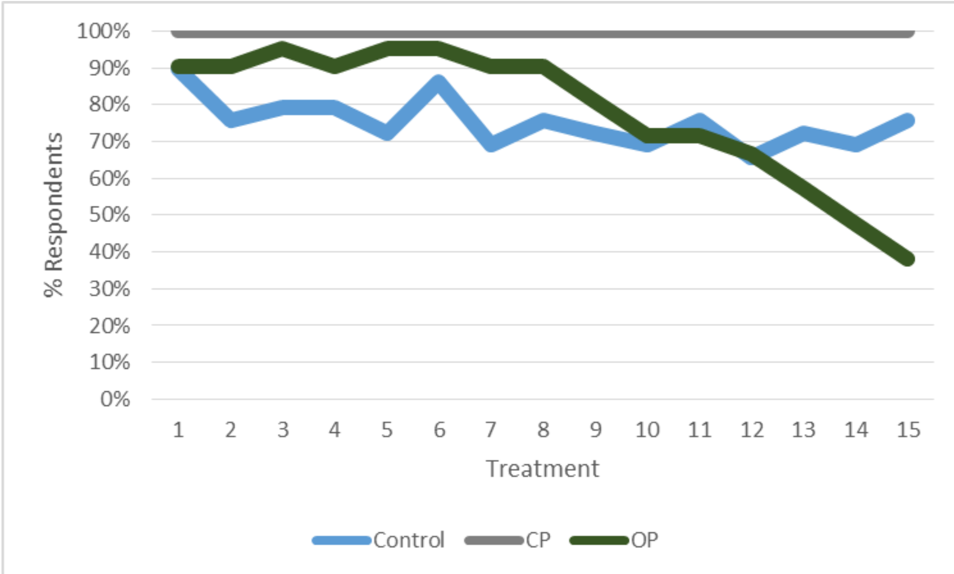

Figure 5. Percentage of self-explanations generated per activity by treatment.

A between-groups analysis, using a series of Kruskal-Wallis tests, reveals a significant difference in completion rates between the closed-prompts treatment, and the control (i.e., non-overt) and open-prompts treatments at multiple stages during the instructional module. More specifically, participants in the control (i.e., non-overt) developed significantly fewer quantities of self-explanations during activities: 2, 3, 4, 5, 7, 8, 9, 10, 13, 14, and 15 (see Table 20). Similarly, participants in the open-prompts treatment) developed significantly fewer quantities of self-explanations during activities: 9, 10, 13, 14, and 15 (see Table 20).

Table 20 Difference in Average Completion Rates of Individual Activities

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Control	0.175	0.03	0.047	0.047	0.018	0.113	0.011	0.03	0.018	0.011	0.03	0.007	0.018	0.011	0.03
Open	0.197	0.197	0.368	0.357	0.368	0.368	0.197	0.197	0.06	0.018	0.018	0.009	0.002	0	0

This analysis continues to suggest that the highly structured nature of closed prompts more effectively promotes the generation of greater quantities of self-explanations when compared to less structured (i.e., open) prompts. Further, the increased quantities of generated self-explanations occur even when there is significantly less time spent generating self-explanations.

Quantity of high-quality of self-explanations generated

Measures related to the quantity of high-quality of self-explanations generated while completing the instructional module were captured for two treatments: (1) closed prompts, and (2) open prompts. Due to the non-observable nature of the self-explanations generated by the control group (i.e., non-overt), no measure was captured. The quantity of high-quality self-explanations generated for the closed-prompts treatment was captured automatically using the Blackboard learning management system. The quantity of high-quality self-explanations generated for the open prompts group was hand coded by the researcher. The mean rank for each treatment was 25.59 for closed prompts and 14.57 for open prompts (see Table 21).

Table 21 Mean Rank of Total Number of High-Quality Self-Explanations

Treatment	N	Mean Rank
Closed	17	25.59
Open	21	14.57

A Mann-Whitney test indicated that the quantity of high-quality self-explanations generated by the closed-prompts treatment *(Mdn=7.0)* was significantly greater when compared to the open-prompts treatment *(Mdn=3.0)*, $U=75$, $p = 0.002$, $r = 0.50$. The effect size was medium. This analysis suggests that the closed-prompts treatment more effectively promoted the generation of high-quality self-explanations when compared to the control (i.e., non-overt) and open-prompts treatments. Results of the analysis are presented in Table 22.

Table 22 Difference in Quantity of High-Quality Self-Explanations

Treatment Comparison	U	Z	N	P	Effect size
Closed vs Open	75	-3.054	38	0.002	0.50

Summary of findings – prompt structure and quantity of high-quality self-explanations

Results of the study revealed that closed prompts promote the generation of greater quantities of high-quality self-explanations when compared to open prompts (see Figure 6). Participants in the closed-prompts treatment developed a greater quantity of high-quality self-explanations *(M=7.5)* when compared to the open-prompts treatment *(M=3.7)*. Furthermore, there was a significant difference in the quantity of high-quality self-explanations generated between treatments.

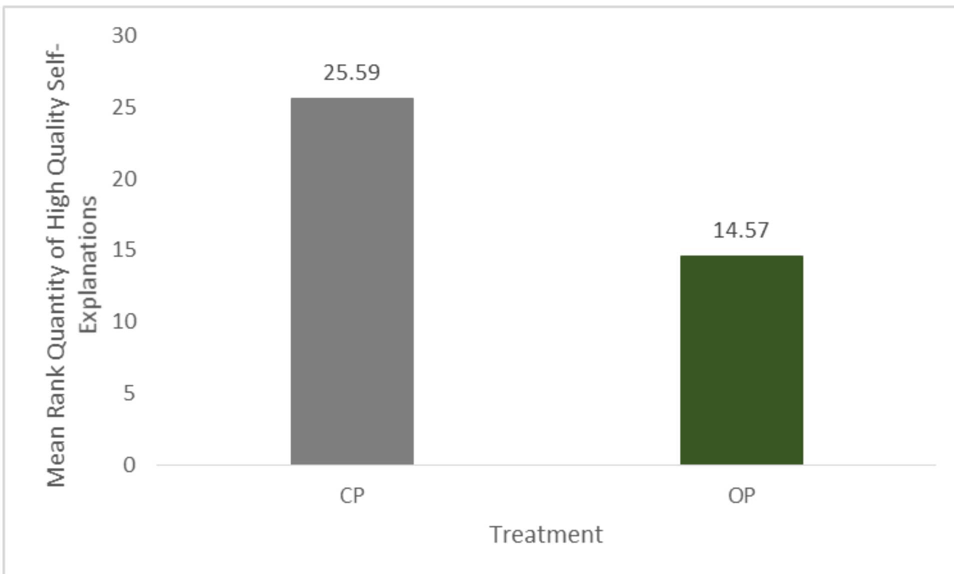

Figure 6. Mean rank quantity of high-quality self-explanations*.

*Control (non-overt) treatment: Quality was not observable.

Quantity of accurate self-explanations generated

Measures related to the accuracy of self-explanations generated while completing the instructional module were captured for two treatments: (1) closed prompts, and (2) open prompts. Due to the non-observable nature of the self-explanations generated by the control (i.e., non-overt) treatment, no measure was captured. The accuracy of self-explanations generated for the closed-prompts treatment were captured automatically using the Blackboard learning management system. The accuracy of self-explanations generated for the open-prompts treatment were hand coded by the researcher. The mean rank for each treatment group was 23.68 for closed prompts and 16.12 for open prompts (see Table 23).

Table 23 Mean Rank of Accuracy of Self-Explanations

Treatment	N	Mean Rank
Closed	17	23.68
Open	21	16.12

A Mann-Whitney test indicated that the quantity of accurate self-explanations generated by the closed-prompts treatment *(Mdn=8.0)* was significantly greater when compared to the open-prompts treatment *(Mdn=6.0)*, $U=107.5$, $p = 0.036$, $r = 0.34$. However, the effect size was small. Results of the analysis are presented in Table 24.

Table 24 Difference in Accuracy of Self-Explanations

Treatment Comparison	U	Z	N	P	Effect size
Closed vs Open	107.5	-2.094	38	0.036*	-0.34

Summary of findings – prompt structure and quantity of accurate self-explanations

Results of the study revealed that closed prompts promote the generation of greater quantities of accurate self-explanations when compared to open prompts. Participants in the closed-prompts treatment developed a greater quantity of accurate self-explanations *(M=8.3)* when compared to the open-prompts treatment *(M=5.1)* (see Figure 7). Further, the analysis revealed a statistically significant difference in the quantity of accurate self-explanations generated between treatments, i.e. the closed-prompts treatment generated significantly more accurate self-explanations when compared to the open-prompts treatment ($U = 107.5$, $Z = -2.094$, effect size $= Z/srt_{(38)} = -0.34$, $p = 0.036$). Again, it should be noted in this case that the effect size was small.

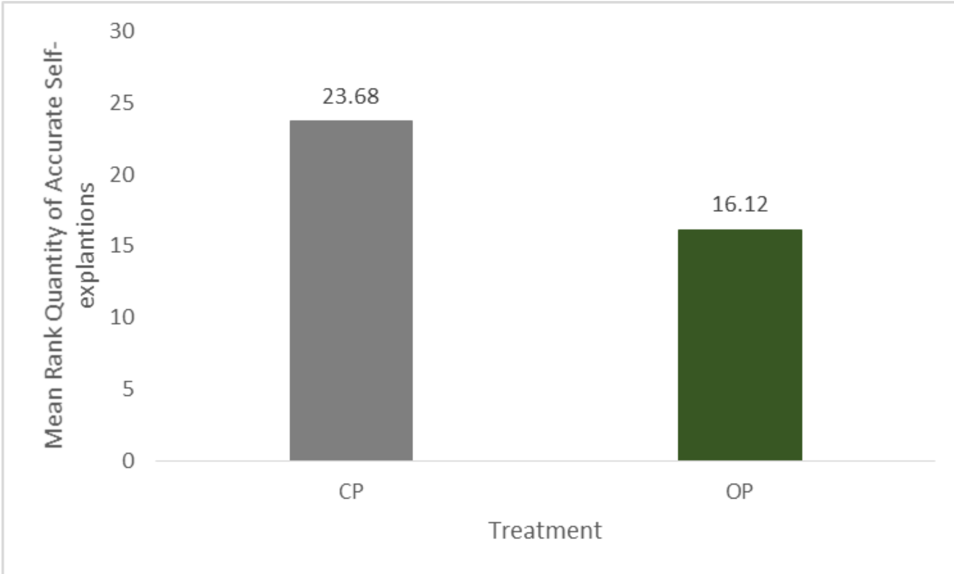

Figure 7. Mean rank of quantity of accurate self-explanations*.

*Control (non-overt) treatment: Accuracy was not observable.

Cognitive load

Measures related to cognitive load were captured upon completion of the instructional module for all treatments. Two specific measures were recorded using the learning management system: (1) intrinsic cognitive load (complexity), and (2) extraneous cognitive load (effort).

Descriptive analysis – cognitive load.

Measures related to the intrinsic cognitive load (complexity) were reported by study participants after completing the instructional module for all treatments (see Table 25).

Table 25 Descriptive Statistics for Intrinsic Cognitive Load (complexity)

	N	Min	Max	Mean	Std. Dev.	Median	Skewness	Kurtosis
All Combined	56	1	9	5.34	2.474	5.5	-0.062	-1.086
Control	28	1	9	4.89	2.572	5.0	0.226	-1.053
Closed	16	2	9	5.81	2.073	6.0	-0.177	-0.988
Open	12	1	9	5.75	2.734	6.0	-0.422	-0.896

Measures related to the extraneous cognitive load (effort) were reported by study participants after completing the instructional module for all treatments (see Table 26).

Table 26 Descriptive Statistics for Extraneous Cognitive Load (effort)

	N	Min	Max	Mean	Std. Dev.	Median	Skewness	Kurtosis
All Combined	56	1	9	4.88	2.313	5.0	0.066	-0.788
Control	28	1	9	4.46	2.186	4.50	0.178	-0.833
Closed	16	1	9	5.31	2.414	5.0	0.198	-0.742
Open	12	1	9	5.25	2.491	5.5	-0.511	-0.220

A visual inspection of the data using histograms (see Appendix O) suggested that data may not be normally distributed. Further, a review of the data in relation to skewness and kurtosis revealed that many of the values were not close to zero (see Table 25). This indicated the data might not be normally distributed. In order to gain statistical evidence, Kolmogorov-Smirnov and Shapiro-Wilk tests were completed. The results of these tests confirmed the assumption that the majority of data was not normally distributed (see Appendix P). Accordingly, all data were analyzed using non-parametric methods.

Intrinsic cognitive load.

A Kruskal-Wallis test indicated that there was no statistically significant difference in the intrinsic cognitive load reported between treatments ($\chi^2(2) = 1.86$, p = 0.395), with a mean rank of 25.55 for the control treatment, a mean rank of 31.34 for the closed-prompts treatment, and a mean rank of 31.58 for the open-prompts treatment. Results of the analysis are presented in Table 27.

Extraneous cognitive load.

A Kruskal-Wallis test indicated that there was no statistically significant difference in the extraneous cognitive load reported between treatments ($\chi^2(2) = 1.63$, $p = 0.443$), with a mean rank of 25.75 for the control treatment, a mean rank of 30.97 for the closed-prompts treatment, and a mean rank of 31.63 for the open-prompts treatment. Results of the analysis are presented in Table 27.

Table 27 Mean Rank of Cognitive Load Reported

Treatment	N	Intrinsic Complexity Mean Rank	N	Extraneous Effort Mean Rank
Control	28	25.55	28	25.75
Closed	16	31.34	16	30.97
Open	21	31.58	12	31.63

Summary of findings – prompt structure and cognitive load

Results of the analysis did not reveal that open prompts exert a higher level of extraneous cognitive load on an individual when compared to closed prompts (see Figure 8). Participants in the closed-prompts treatment reported the highest level of extraneous cognitive load *(M=5.31)*. This was followed by participants in the open-prompts treatment *(M=5.25)*. Finally, participants in the control (non-overt) treatment reported the lowest level of cognitive load *(M=4.50)*. A Kruskal-Wallis H test revealed that extraneous cognitive load was not significantly affected by treatment: $\chi^2(2) = 1.630$, $p = 0.443$. The analysis suggests that the generation of self-explanations is a moderately demanding cognitive learning activity, which is consistent with previous research (Wylie & Chi, 2014).

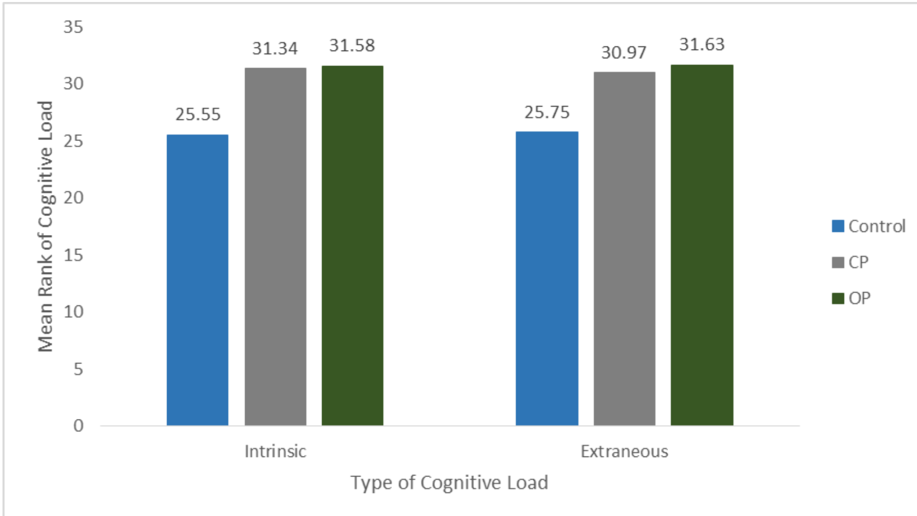

Figure 8. Mean rank of intrinsic and extraneous cognitive load by treatment.

Activity Type – Overt / Non-overt

In this section, an analysis of the results pertaining to the effects different types of learner activity (i.e., overt vs non-overt) have on learning outcomes is presented. During the experiment, two forms of overt learner activity (i.e., the generation of self-explanations) were promoted via the use of different types of instructional prompt: (1) selecting a menu-based self-explanation (i.e., closed prompts), and (2) typing a self-explanation (i.e., open prompts). Non-overt activity (i.e., the control treatment) was promoted via the presentation of a self-explanation prompt, however, no overt response was required. Instead, participants in this treatment were simply asked if they generated a self-explanation while completing an activity.

Descriptive analysis – activity type

Similarly to the analysis presented for the research question related to prompt type and learning outcomes, learning outcomes were defined as the difference between pretest and posttest assessment scores. Measures related to the difference in scores were calculated for all treatments (see Table 28).

Table 28 Descriptive Statistics for Difference Between Pretest and Posttest

Variable	N	Min	Max	Mean	Std. Dev.	Median	Skewness	Kurtosis
All Combined	67	-14.0	12.0	1.34	4.194	1.0	-0.522	2.053
Control	29	-14.0	8.0	0.41	4.371	1.0	-1.141	3.202
Closed	17	-2.0	10.0	3.06	2.861	3.0	0.659	0.919
Open	21	-6.0	12.0	1.24	4.582	0.0	0.396	0.131

A visual inspection of the data using histograms (see Appendix O) suggested that data may not be normally distributed. Further, a review of the data in relation to skewness and kurtosis revealed that many of the values were not close to zero (see Table 27). This indicated the data might not be normally distributed. In order to gain statistical evidence, Kolmogorov-Smirnov and Shapiro-Wilk tests were completed. The results of these tests confirmed the assumption that the majority of data was not normally distributed (see Appendix P). Accordingly, all data were analyzed using non-parametric methods.

Between-groups analysis – activity type

A Kruskal-Wallis test, the non-parametric equivalent of an ANOVA test, indicated that there was no statistical difference in learning outcomes between treatment groups ($\chi^2(2) = 5.147$, $p = 0.076$), with a mean rank of 30.36 for the control treatment, a mean rank of 43.15 for the closed-prompts treatment, and a mean rank of 31.62 for the open-prompts treatment. Results of the analysis are presented in Table 29.

Table 29 Mean Rank of Test Gain Scores by Treatment

Group	N	Mean Rank
Control	29	30.36
Closed	17	43.15
Open	21	31.62

Within-group analysis – activity type

In order to understand the within-group differences between pretest and posttest scores, each group was examined individually, using a Wilcoxon signed-rank test, the non-parametric equivalent of a dependent t-test (or repeated measures ANOVA). The Wilcoxon signed-rank test indicated that the difference between the pretest and posttest scores for the closed prompts – overt activity treatment (*Mdn=3.0,* Z= -3.218, $p < 0.000$) was statistically significant. Differences between pretest and posttest scores for the control (non-overt activity) (*Mdn= 1.0,* Z= -0.988, $p < 0.332$) and open prompts (i.e., overt activity) treatment (*Mdn= 0.0,* Z= -1.169, $p < 0.243$) were not significantly different. The effect size for the closed-prompts treatment was medium (-0.78) (see Table 30).

Table 30 Difference Between Pretest and Posttest Scores by Treatment

Treatment	Z	N	P	Effect size
Control (Non-overt)	-0.988	29	0.332	-0.183
Closed - Overt	-3.218	17	0.000	-0.780
Open - Overt	-1.169	21	0.243	-0.255

Summary of findings related to activity type and learning outcomes

Results of the study revealed that overt activity more effectively drives learning outcomes when compared to non-overt activity, only in the case of the closed-prompts treatment (see Figure 9). Participants in the closed-prompts treatment had the largest learning gain between pretest and posttest assessments *(M=3.06)*. This was followed by the open-prompts treatment *(M=1.24)*. Finally, the control (i.e., non-overt) treatment had the smallest learning gain *(M=0.41*). Learning outcomes were significantly affected for the closed-prompts treatment, however, the open prompts and control treatments (i.e., non-overt) were not significantly affected (CP: $p = 0.000$; OP: $p = 0.243$; NO: $p = 0.332$). The effect size for the closed-prompts treatment was medium (CP Effect Size-0.780).

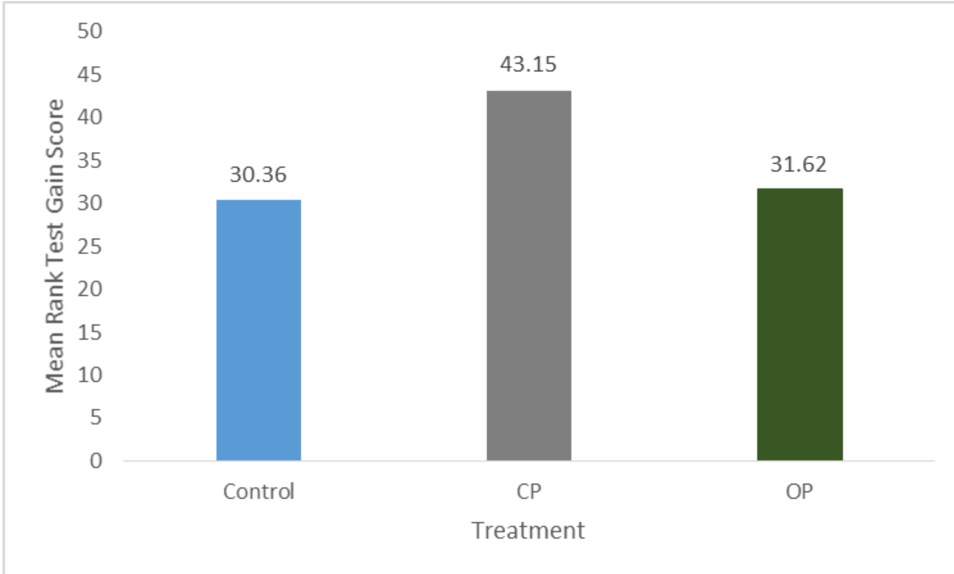

Figure 9. Mean rank of test gain scores by treatment.

Self-efficacy

In this section, an analysis of the results pertaining to the effects the self-explanation learning strategy has on learner self-efficacy is presented. As outlined previously in the literature review, self-efficacy drives self-regulatory behaviors, i.e. the evaluation of learning progress, that are closely linked to the attainment of learning goals (Schunk, 1990; Zimmerman, 1990). The purpose of this research question was to measure if any increase or decrease occurred in relation to learner self-efficacy as a result of the self-explanation activity.

Two measures related to self-efficacy were captured: (1) perceived knowledge level within the domain; and (2) confidence level related to knowledge within the domain. Both measures were captured prior to beginning the instructional module, and immediately after completing the instructional module, using the Blackboard learning management system.

Similarly to the process outlined for the learning outcomes measure, the difference between pre-instructional and post-instructional measures of self-efficacy were calculated.

Further, the availability of data for three treatments enabled the researcher to conduct both a between-groups and a within-group analysis.

Descriptive analysis – self-efficacy

Measures related to domain knowledge level before completing the instructional module were captured for all treatments (see Table 31).

Table 31 Descriptive Statistics for Domain Knowledge Level Pre-Instruction

	N	Min	Max	Mean	Std. Dev.	Median	Skewness	Kurtosis
All Combined	66	1	9	4.33	2.165	4.0	0.239	-0.627
Control	29	1	9	4.0	2.035	4.0	0.464	-0.050
Closed	16	1	8	4.06	2.205	3.50	0.336	-1.031
Open	21	1	9	5.0	2.258	5.0	-0.144	-0.283

Measures related to domain knowledge level after the instructional module were captured for all treatments (see Table 32).

Table 32 Descriptive Statistics for Domain Knowledge Level Post-Instruction

	N	Min	Max	Mean	Std. Dev.	Median	Skewness	Kurtosis
All Combined	56	1	9	4.05	2.511	3.0	0.487	-1.029
Control	28	1	9	3.96	2.168	3.0	0.636	-0.366
Closed	16	1	9	4.31	2.750	3.50	0.330	-1.438
Open	12	1	9	3.92	3.088	2.50	0.538	-1.530

Measures related to the difference between domain knowledge level both before and after the instructional module were calculated as gain scores for all treatments (see Table 33).

Table 33 Descriptive Statistics for Difference in Domain Knowledge Level

	N	Min	Max	Mean	Std. Dev.	Median	Skewness	Kurtosis
All Combined	56	-6.0	4.0	-0.11	1.603	0.0	-0.863	3.176
Control	28	-6.0	3.0	-0.14	1.671	0.0	-1.551	4.882
Closed	16	-3.0	4.0	0.25	1.571	0.0	0.472	1.794
Open	12	-4.0	1.0	-0.50	1.508	-0.50	-1.051	1.328

Measures related to self-confidence level before the instructional module were captured for all treatments (see Table 34).

Table 34 Descriptive Statistics for Self-Confidence Level Pre-Instruction

	N	Min	Max	Mean	Std. Dev.	Median	Skewness	Kurtosis
All Combined	66	1	9	4.41	2.327	5	0.111	-1.033
Control	29	1	9	4.14	2.356	4.0	0.351	-0.800
Closed	16	1	8	4.44	2.337	5.0	-0.143	-1.398
Open	21	1	9	4.76	2.343	5.0	-0.018	-0.853

Measures related to self-confidence level after completing the instructional module were captured for all treatments (see Table 35).

Table 35 Descriptive Statistics for Self-Confidence Level Post-Instruction

	N	Min	Max	Mean	Std. Dev.	Median	Skewness	Kurtosis
All Combined	54	1	9	4.11	2.589	3.5	0.367	-1.28
Control	28	1	9	4.14	2.368	3.5	0.466	-0.933
Closed	15	1	9	4.67	2.870	5.0	0.010	-1.600
Open	11	1	8	3.27	2.760	2.0	0.909	-1.007

Measures related to the difference between self-confidence levels both before and after the instructional module were calculated as gain scores for all treatments (see Table 36).

Table 36 Descriptive Statistics for Difference in Self-Confidence Level

	N	Min	Max	Mean	Std. Dev.	Median	Skewness	Kurtosis
All Combined	54	-6.0	3.0	-0.09	1.457	0.0	-1.087	4.169
Control	28	-6.0	3.0	-0.11	1.663	0.0	-1.482	5.034
Closed	15	-1.0	2.0	0.33	1.113	0.0	0.665	-0.870
Open	11	-3.0	1.0	-0.64	1.206	-1.0	-0.446	0.129

A visual inspection of the data using histograms (see Appendix O) suggested that data may not be normally distributed. Further, a review of the data in relation to skewness and kurtosis revealed that many of the values were not close to zero (see above). This indicated the data might not be normally distributed. In order to gain statistical evidence, Kolmogorov-Smirnov and Shapiro-Wilk tests were completed. The results of these tests confirmed the assumption that the majority of data was not normally distributed (see Appendix P). Accordingly, all data were analyzed using non-parametric methods. In order to perform the non-parametric equivalent of a repeated measure ANOVA amongst three groups, a combination of between-groups and within-group analyses was applied.

Between-groups analysis – self-efficacy

A Kruskal-Wallis test indicated that there was no statistically significant difference in self-efficacy (i.e., pertaining to knowledge) between treatments ($\chi^2(2) = 1.11$, $p = 0.574$), with a mean rank of 28.88 for the control treatment, a mean rank of 30.81 for the closed-prompts treatment, and a mean rank of 24.54 for the open-prompts treatment. Similarly, a Kruskal-Wallis test indicated that there was no statistically significant difference in self-efficacy (i.e., pertaining to confidence) between treatments ($\chi^2(2) = 3.19$, $p = 0.203$), with a mean rank of 28.29 for the control treatment, a mean rank of 31.07 for the closed-prompts treatment, and a mean rank of 20.64 for the open-prompts treatment. Results of the analysis are presented in Table 37.

Table 37 Mean Rank of Self-Efficacy Gain Scores by Treatment

Treatment	N	Knowledge Mean Rank	Confidence Mean Rank
Control	28	28.88	28.29
Closed	16	30.81	31.07
Open	12	24.54	20.64

Within-group analysis – self-efficacy

In order to gain an understanding of the within-group differences, each treatment group was examined individually, using the non-parametric equivalent of a dependent t-test. Wilcoxon signed-rank tests were performed for both self-efficacy measures to test differences within one group at a time. For this test, the pre-instructional module and post-instructional module were treated as separate variables.

In the case of knowledge level, a Wilcoxon signed-rank test indicated that there was no statistically significant difference between the pre and post instructional module scores for all treatments (control: *Mdn= 0.0, Z -0.84, p = 0.939*; closed prompts: *Mdn= 0.0,* Z= -0.66, *p = 0.535*; open prompts: *Mdn= -0.5, Z=-1.026, p = 0.408*). Results of the analysis related to knowledge level scores are presented in Table 38.

Table 38 Difference Between Pre-Instruction and Post-Instruction Knowledge

Treatment	Z	N	P	Effect size
Control	-0.84	28	0.939	-0.16
Closed	-0.664	16	0.535	-0.17
Open	-1.026	12	0.408	-0.30

In the case of confidence level, a Wilcoxon signed-rank test indicated that there was no statistically significant difference between the pre and post instructional module scores for all treatments (control: *Mdn= 0.0, Z -0.073, p = 0.947*; closed prompts: *Mdn= 0.0, Z= -1.387, p = 0.188*; open prompts: *Mdn= -1.0, Z = -1.687, p = 0.180*). Results of the analysis are presented in Table 39.

Table 39 Difference Between Pre-Instruction and Post-Instruction Confidence

Treatment	Z	N	P	Effect size
Control	-0.073	28	0.947	-0.01
Closed	-1.387	15	0.188	-0.36
Open	-1.611	11	0.180	-0.49

Summary of findings – self-explanation and self-efficacy

Results of the analysis revealed that participants in the closed-prompts treatment reported a slight increase in the self-efficacy measure related to knowledge after completing the instructional module; participants in the control (i.e., non-overt) and open-prompts treatments both reported a slight decrease in this measure. Similarly, participants in the closed-prompts treatment reported a slight increase in the self-efficacy measure related to confidence after completing the instructional module. In contrast, participants in the control (i.e., non-overt) and open-prompts treatments both reported a slight decrease in this measure. No significant difference between each of these measures was revealed (see Figure 10).

Figure 10. Mean rank of self-efficacy gain scores by treatment.

Summary of Findings

In summary, this research study investigated application of the self-explanation learning strategy when used during an instructional simulation. Three main areas were the focus of the study: (1) the effect different types of self-explanation prompt have on application of the learning strategy and learning outcomes, (2) the effect different types of learning activity (i.e., overt vs non-overt) have on learning outcomes, and (3) the effect the self-explanation learning strategy has on learner self-efficacy (see Table 40).

In relation to prompt type (i.e., closed vs open), the open-prompts treatment spent a significantly greater amount of time generating self-explanations when compared to closed prompts and the control treatment. However, the closed-prompts treatment developed greater quantities of self-explanations during the instructional module when compared to the open-prompts treatment and the control treatment. Similarly, the closed-prompts treatment resulted in learners significantly generating greater quantities of high-quality self-explanations and accurate self-explanations during the instructional module when compared to both the open-prompts treatment and the control treatment. No significant difference in the cognitive load required to generate self-explanations was revealed between treatments. All treatments reported a moderately high level of cognitive load which is consistent with previous research. In terms of the learning outcomes achieved only the closed-prompts treatment saw a significant gain between scores on a pretest and posttest assessment. Each of these measures suggest that closed prompts are more effective then open prompts in driving application of the self-explanation learning strategy and ultimately learning outcomes when used with a computer-based simulation.

In relation to activity type (i.e., overt vs non-overt), the findings were less conclusive. The closed prompts – overt activity treatment was the only treatment to achieve a significant learning gain when pretest and posttest assessment performance was measured. No significant learning gain was measured for the open prompts – overt activity treatment and the control – no-overt activity treatment. This suggests that the type of self-explanation prompt (i.e., closed/open) presented to a learner during an instructional simulation is more effective in driving learning outcomes then the type of activity (i.e., overt/non-overt) that a learner engages in.

Finally, in relation to learner self-efficacy, two measures were captured (i.e., knowledge level and confidence level) both before and after the instructional module. No significant difference for either self-efficacy measure was revealed between treatments. Further, a self-efficacy gain score was calculated for each measure for each treatment. No significant difference between the pre-instruction and post-instruction measures was revealed. Therefore, results of this study suggest that using the self-explanation strategy during a computer-based simulation does not have a significant effect on learner self-efficacy.

Table 40 Summary of Findings

Research Question	Findings
1. During an instructional simulation, what effect do Closed and Open self-explanation prompts have on learning outcomes, application of the self-explanation learning strategy, and cognitive load?	• Only closed-prompts treatment saw a significant gain between scores on a pretest and posttest assessment. • Open-prompts treatment spent a significantly greater amount of time generating self-explanations. • Closed-prompts treatment developed significantly greater quantities of when compared to open prompts and control: - self-explanations (total) - high-quality self-explanations - accurate self-explanations • All treatments reported a moderately high level of cognitive load. No significant difference between treatments.
2. During an instructional simulation, what effect does overt and non-overt learner activity have on learning outcomes?	• Closed prompts – overt activity treatment was the only treatment to achieve a significant learning gain when pretest and posttest assessment performance was measured. • No significant learning gain was measured for the open prompts – overt activity
3. During an instructional simulation, what effect does self-explanation have on learner self-efficacy?	• No significant difference for either self-efficacy measure (knowledge and confidence) was revealed between treatments. • No significant difference between the pre-instruction and post-instruction self-efficacy measures was revealed.

CHAPTER IV

DISCUSSION AND CONCLUSION

This chapter presents a discussion of the findings from this specific study within the context of previous research in the area. Further, limitations to these findings are presented. Finally, implications for future research are discussed.

Prompt Type

The findings of this study suggest that within the context of an instructional module, centered on a computer-based instructional simulation, closed (i.e., structured) prompts more effectively drive application of the self-explanation learning strategy and ultimately greater learning outcomes when compared to open (i.e., unstructured) prompts. More specifically, closed prompts promote the generation of greater quantities of self-explanations, greater quantities of high-quality self-explanations, and greater quantities of accurate self-explanations. Ultimately, this results in greater learning gains. These findings align with previous research in the area that focused on non-simulation based instructional materials (Chi et al., 1989; O'Reilly et al., 1998; Renkl et al., 1998). However, the findings also suggest that while participants in the closed-prompts treatment achieve greater learning outcomes when compared to those in the open-prompts treatment, the closed-prompts treatment spent less time generating self-explanations. This runs contrary to previous research in the area (Roy & Chi, 2005). One possible interpretation of these findings is that the quality of self-explanation activity (i.e., the generation of high-quality self-explanations) is more important than the quantity of self-explanation activity (i.e., time spent generating self-explanations) in driving learning outcomes. Another, possible interpretation of these findings is that closed prompts drive more focused self-explanation learning activity when compared to open prompts. The study outlined in this dissertation does not provide a clear basis for either of these assumptions and therefore further research is suggested (see implications for future research).

Overt Vs Non-overt Learner Activity

One of the underlying assumptions associated with the iCAP framework is that overt (i.e., observable) learner activity will be more effective in driving learning outcomes when compared to non-overt (i.e., non-observable) learning activity (Chi & Wylie, 2014). However, the findings of this study were inconclusive when this assumption was tested. The closed prompts – overt treatment achieved a significant gain in learning when the difference in performance scores on pretest and posttest assessments were compared. The open prompts – overt, and control – non-overt treatments, did not achieve significant learning gains when the difference in pretest and posttest assessments were calculated.

One possible interpretation of these findings is that the structure of a self-explanation prompt appears to have a greater influence on application of the self-explanation learning strategy and attainment of learning outcomes than the type of activity (i.e., overt vs non-overt) that a learner engages in. Interestingly, no significant difference in the extraneous cognitive load reported was revealed between treatments. This appears to run contrary to the literature related to cognitive load (Sweller et al., 2011). Similarly, the assumption related to overt/non-overt activity underlying the iCAP framework does not seem to hold, at least when applied to an instructional context centered on a computer-based simulation.

This study does not provide conclusive evidence to support or refute the efficacy of overt activity when compared to non-overt activity. Rather, it provides direction for future research. Possible areas for related research are outlined in more detail in the implications for future research section below.

Limitations

When considering the findings associated with this specific study, it is important to consider several limitations. First, the scope of the study was limited. Participants in the study were exposed to one instructional module focused on declarative knowledge and simple problem solving skills. Higher-order thinking skills were absent from the learning objectives for the instructional module.

Second, the duration of time taken to complete this experiment was limited to approximately sixty minutes. This timeframe varies from more common instructional contexts (i.e., a semester long college level course). Further, the duration of the experiment did not allow for the measurement of the long-term retention and comprehension of knowledge and skills acquired. As a result, we should use caution when generalizing these findings to all instructional contexts.

Finally, throughout the experiment, the cognitive processes that participants engaged in were unobservable. Having a greater visibility into these processes would enable us to better understand these findings. Further explanation on this topic is discussed in the implications for future research section below.

Implications for Future Research

In this section implications for further research are presented. Three major areas related to further research on using the self-explanation learning strategy in conjunction with a computer-based instructional simulation are discussed: (1) observing learner activity, (2) comparing different types of closed prompt, and (3) promoting the accuracy of self-explanations generated.

Observing learner activity

During this experiment, participants interacted with the computer-based instructional module, without assistance from an instructor or facilitator. Further, all cognitive activity was internalized (i.e., not overt). One approach that is likely to provide insight into this activity, would be to use a mixed method study and apply a think-aloud procedure (Van Someren, Barnard, & Sandberg, 1994). When using a think-aloud procedure, participants verbalize cognitive activity (i.e., overtly explaining observed causal relationships) in a manner that is observable. Using a think-aloud procedure will provide greater visibility into the cognitive activity that a learner engages in when interacting with instructional technologies and learning strategies (i.e., computer-based simulations and self-explanation). Ultimately, this approach would enable researchers to observe learner activity with a focus on both the quality and accuracy of the self-explanations generated.

Comparing different types of closed prompt

In terms of the quality of self-explanations generated, the analysis suggests that closed prompts foster the generation of greater quantities of high-quality self-explanations when compared to open prompts. During the experiment, participants in the closed-prompts treatment generated self-explanations by selecting a self-explanation statement from a range of options presented. The majority of the self-explanations presented were high-quality principle-based self-explanations (Chi & VanLehn, 1991). Only two activities out of the fifteen activities presented to the closed-prompts treatment during the instructional module promoted the generation of low-quality self-explanations (i.e. summarizing onscreen action).

In the open-prompts treatment, participants generated significantly less high-quality self-explanations. It would seem logical to assume that higher levels of cognitive load placed on an individual impact the generation of high-quality self-explanations (Conati & Vanlehn, 2000; Wylie & Chi, 2014). However, when the treatments were compared, the analysis revealed that there was not a significant difference in the effort (i.e., extraneous cognitive load) reported by learners upon completing the instructional module.

Using the think-aloud procedure outlined previously, a study utilizing only closed prompts that differ according to the quality of the information presented may provide greater insight into the cognitive activity learners engage in while self-explaining. More specifically, the proposed study would present only low-quality self-explanation prompts (i.e., a summary of screen activity) to one treatment, while a second treatment would only be presented with high-quality self-explanations (i.e., principle-based self-explanations).

Similarly, a subsequent study comparing different types of high-quality self-explanation prompt, i.e. principle-based, goal-operator explications, and anticipative-reasoning (Renkl, 1997) would be useful. Each prompt type promotes a different type of cognitive activity. For example, principle-based self-explanations focus on the underlying principles of a concept, goal-operator self-explanations focus on causal relationships, and anticipative-reasoning self-explanations promote forward looking knowledge construction. Observing the activity that results from different types of self-explanation prompt would provide greater insight into the nature (i.e., type) of the prompts that should be developed to most effectively drive learning outcomes.

Promoting accuracy of self-explanations

Learners commonly experience inaccuracies in comprehension even after engaging in formal instruction (Chi, Roscoe, Slotta, Roy, & Chase, 2012). In the case of science focused education, similar to the computer-based instructional module used in this study, these misconceptions are usually related to processes that underlie the domain (Dupin & Johsua, 1984;

Grotzer & Sudbury, 2000; Perkins & Grotzer, 2005; Reiner, Slotta, Chi, & Resnick, 2000). Numerous instructional interventions designed to remediate misconceptions have been tested without a great degree of success (Chi & Ohlsson, 2005; Chi et al., 2012; Confrey, 1990). Therefore, it seems reasonable to suggest that further investigation into the effect that different types of self-explanation prompt have on promoting the generation of accurate self-explanations and by extension reducing misconceptions is required.

The analysis suggests that closed prompts promote the generation of greater quantities of accurate self-explanations when compared to open prompts. Participants in the study only received guidance in relation to monitoring the accuracy of the self-explanations generated while viewing a tutorial on how to use the self-explanation learning strategy prior to beginning the instructional module. The extent to which individuals actively evaluated the accuracy of the information presented via self-explanation prompts during the instructional module is unknown. Utilizing the think-aloud procedure, as outlined previously, will provide greater insight into this process. However, an examination of how learner behavior may be shaped via the provision of prompts designed to promote more accurate comprehension is also likely to provide value.

Prompts that are specific to processes

The existence of two types of process has been identified in the related literature: (1) sequential, and (2) emergent. Sequential processes are defined by a sequence of events that progress in a linear manner towards an outcome. Emergent processes are defined by the interaction of non-sequential events that result in an outcome. Emergent processes are commonly found in science-related domains (Chi & Ohlsson, 2005). A common cause of miscomprehensions related to emergent processes are the incorrect associations made between the inter-level attributes (i.e., the sub-events and agents) of an emergent process (Chi et al., 2012). A potential solution to counteract these incorrect associations may be to prompt learners to focus on the relationships between these inter-level attributes in an effort to understand the interactions that occur, and how they relate to the outcomes of the process. In essence, these prompt types will likely mirror the principle-based and goal-operator type self-explanations previously mentioned (Renkl, 1997).

Prompts that "Nudge" behavior

Finally, the inclusion of simple prompts designed to promote reflection on the accuracy of the self-explanations generated may also be effective. This type of behavior closely aligns with self-regulatory activities that are associated with driving learning outcomes (Bielaczyc et al., 1995; Eom & Reiser, 2000; Zimmerman & Pons, 1986). In the book *Nudge* (Thaler & Sunstein, 2009) the authors offer suggestions on how to change human behavior via the provision of "nudges". In simple terms, the authors suggest that offering choices to individuals can promote desired behaviors. Reinforcing those choices by offering examples as to how they can benefit outcomes, further increase the chances that the desired behaviors will be adopted. An example of this within the instructional context would be the provision of prompts that offer learners the opportunity to check the options that they have selected via menu-based self-explanations. Further, data could be provided on the accuracy of selections made throughout the instructional module, in an effort to promote greater self-regulatory activity.

All of the research suggestions outlined in this chapter focused on designing and testing self-explanation prompts that are specific to a knowledge domain (e.g., science) or sub-domain (e.g., Chemistry). Further, these research suggestions draw primarily from literature related to the design and development of instruction. This final suggestion borrows from research within the domain of behavioral economics, in an effort to construct general prompts focused on encouraging “good” learning behaviors. To date, it appears that little research within the field of instructional design and educational technology has been influenced by this domain. Such investigation will no doubt broaden the horizons of our field.

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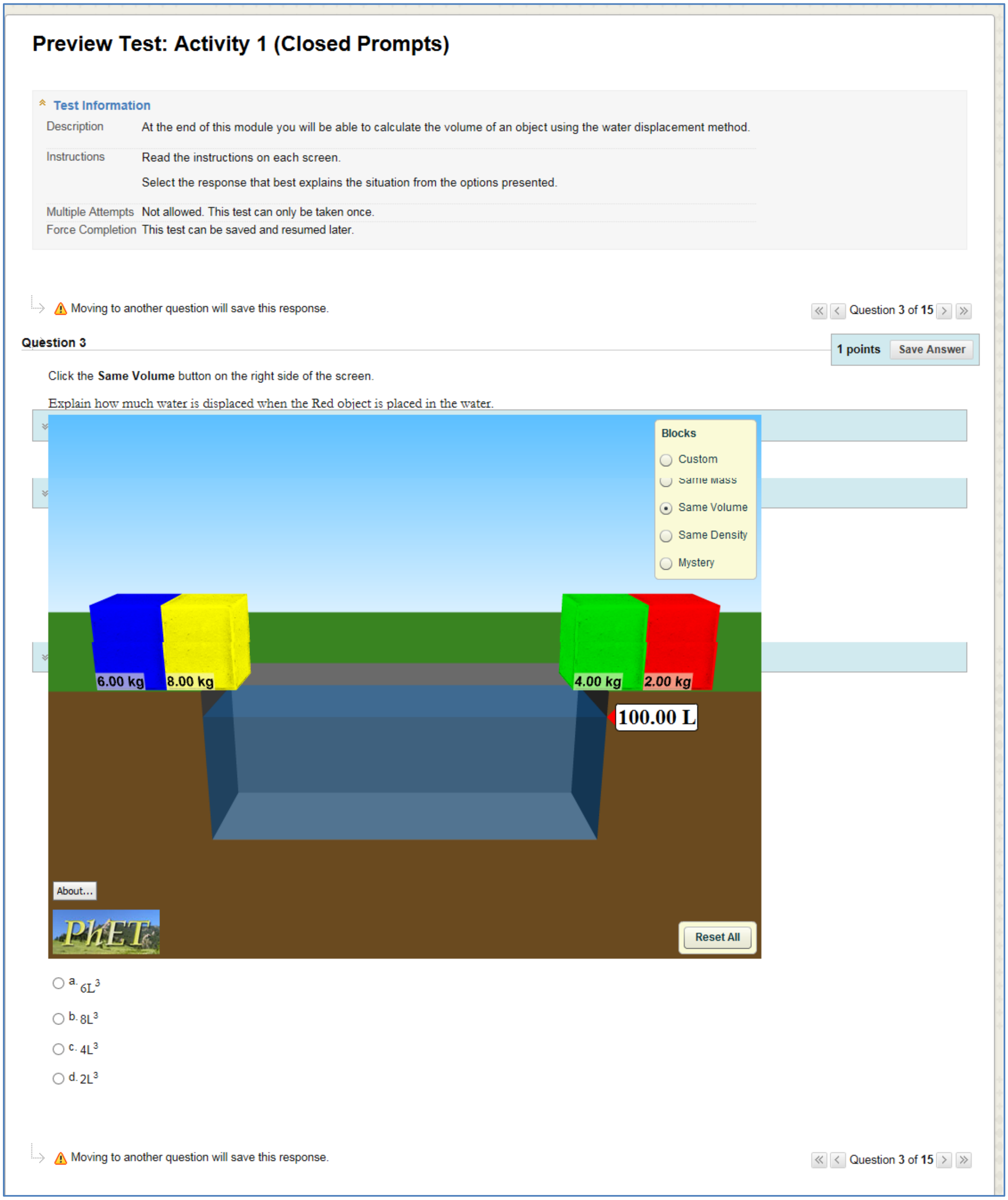
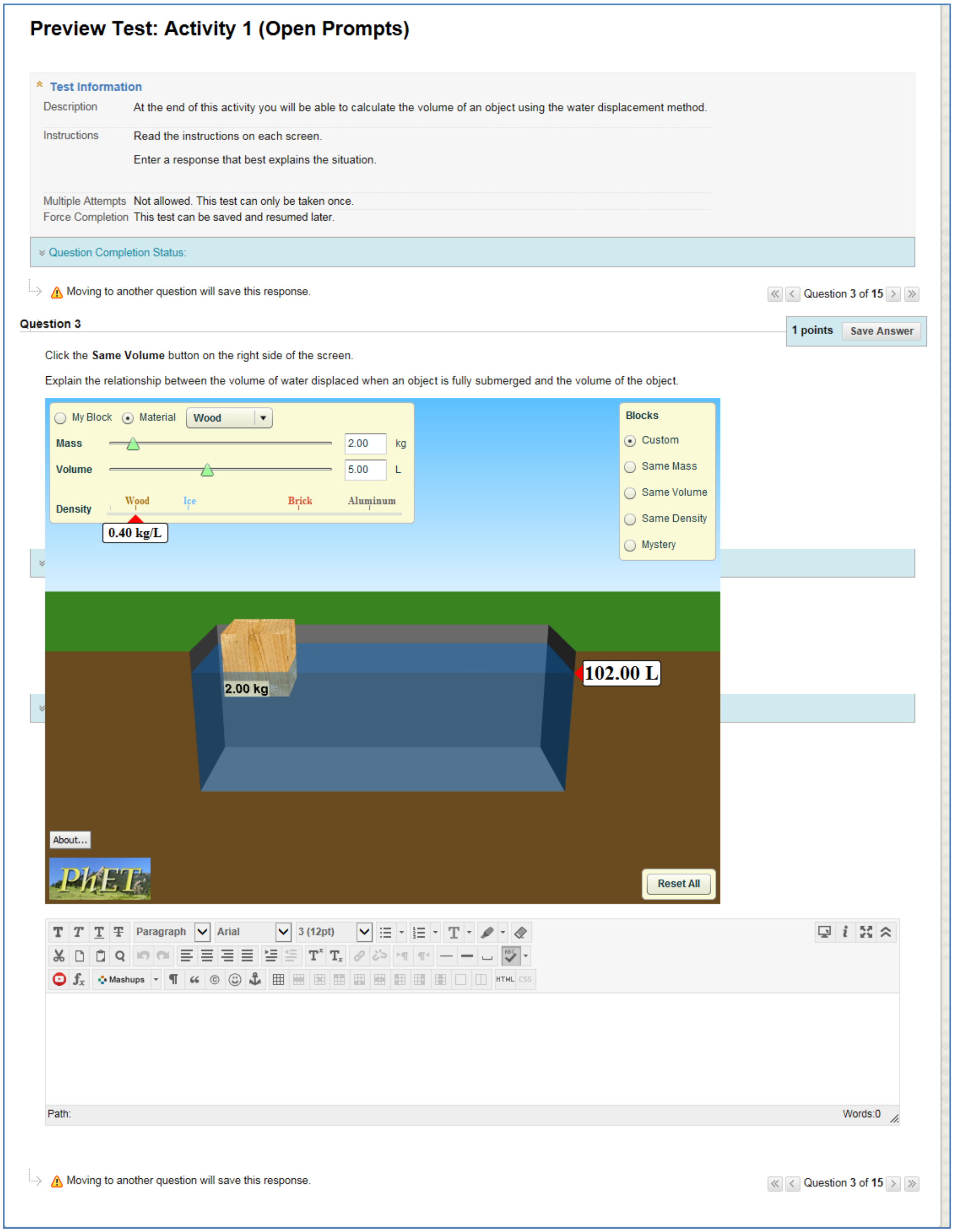
APPENDICES

Appendix A. Examples of Prompt by Treatment

Closed-Prompt Example: Closed-Prompts Overt-Response Treatment



Open-Prompt Example: Open-Prompts Overt-Response Treatment



Prompt Example: No-Overt Response Treatment

Preview Test: Activity 1 (No Overt Response)

Test Information

Description	At the end of this activity you will be able to calculate the volume of an object using the water displacement method.
Instructions	Read the instructions on each screen. Select the response to acknowledge the generation of self-explanation.
Multiple Attempts	Not allowed. This test can only be taken once.
Force Completion	This test can be saved and resumed later.

Moving to another question will save this response.

Question 3 of 15

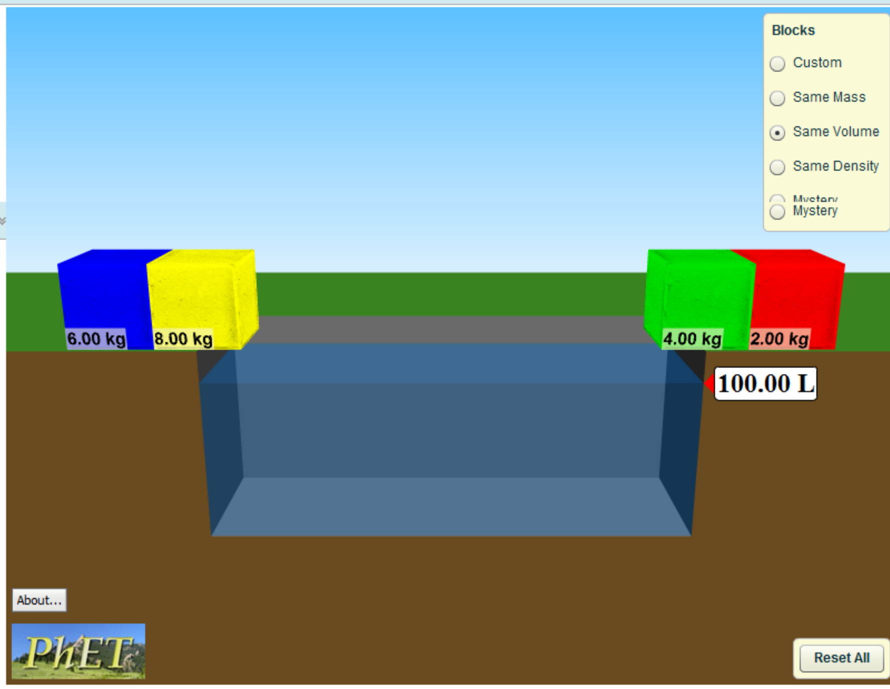
Question 3

1 points Save Answer

Click the **Same Volume** button on the right side of the screen.

Explain the relationship between the volume of water displaced when an object is fully submerged and the volume of the object.

Question Completion Status:



Yes

No

Moving to another question will save this response.

Question 3 of 15

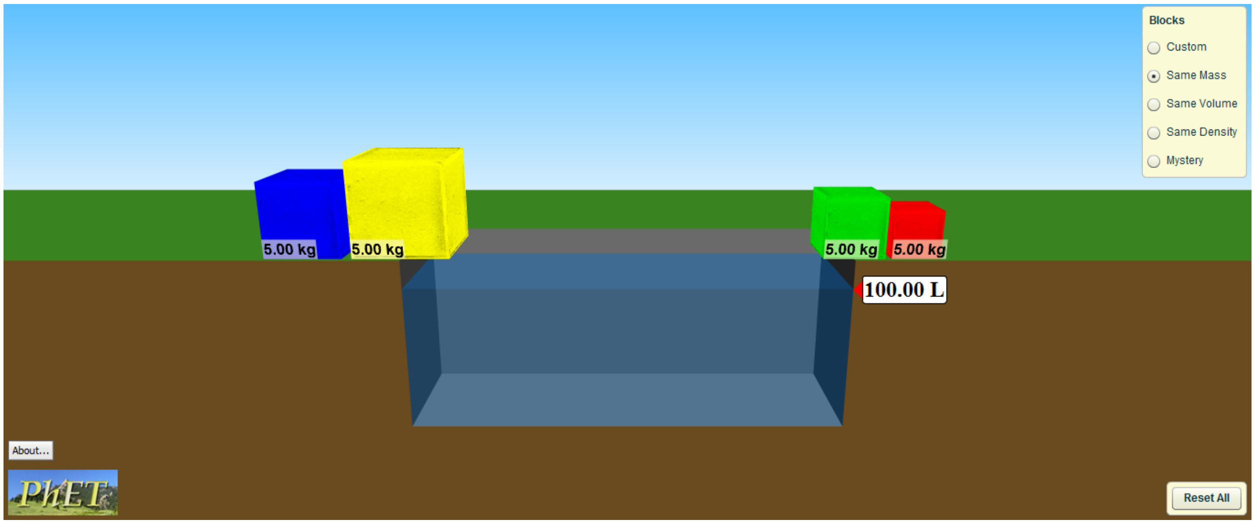
Appendix B. Self-explanation Tutorial

Screenshot of the self-explanation tutorial.

Appendix C. Density Simulation

Screen shot of the simulation as it is hosted online. Use this link to view the density simulation:

https://phet.colorado.edu/en/simulation/density



Appendix D. Instructional Activities

The following instructional activities were presented to each treatment. The only difference between treatments was the structure of the prompt (see Appendix A).

1. Explain how much water is displaced when the Green object is placed in the water:

   a) $2L^3$
   b) $4L^3$*
   c) $6L^3$
   d) $8L^3$

2. Explain how much water is displaced when the Red object is placed in the water:

   a) $2L^3$
   b) $4L^3$
   c) $5L^3$*
   d) $8L^3$

3. Explain the relationship between the volume of the Red object that is below the water when the object is floating and the volume of water displaced by the object when floating.

   a) The volume of the Red object that is below the water when the object is floating is equal to the volume of the water displaced by the object when floating.*
   b) The volume of the Red object that is below the water when the object is floating is less than the volume of the water displaced by the object when floating.
   c) The volume of the Red object that is below the water when the object is floating is greater than the volume of the water displaced by the object when floating.

4. Given that the density (D) of the Red object is 0.8 kg/L^3 and the mass is 1 kg. Explain how you calculate the volume of the object with this information. (Hint use the water displacement method to verify your answer)

   a) Divide the density (D) of the object by the mass (M) of the object to calculate the volume (V=D/M).
   b) Divide the mass (M) of the object by the density (D) of the object to calculate the volume (V=M/D).*
   c) Multiply the mass (M) of the object by the density (D) of the object to calculate the volume (V=MD).

5. Given that the density (D) of the Green object is 0.8 kg/ L^3 and the mass is 2 kg. Explain how you calculate the volume of the object with this information. (Hint use the water displacement method to verify your answer.)

    a) Multiply the mass (M) of the object by the density (D) of the object to calculate the volume (V=MD).
    b) Divide the mass (M) of the object by the density (D) of the object to calculate the volume (V=M/D).*
    c) Divide the density (D) of the object by the mass (M) of the object to calculate the volume (V=D/M).

6. Given that the density (D) of the Red object is 4.0 kg/L3 and the mass is 5 kg. Explain how you calculate the volume of the object with this information. (Hint use the water displacement method to verify your answer.)

    a) Divide the density (D) of the object by the mass (M) of the object to calculate the volume (V=D/M).
    b) Multiply the mass (M) of the object by the density (D) of the object to calculate the volume (V=MD).
    c) Divide the mass (M) of the object by the density (D) of the object to calculate the volume (V=M/D).*

7. Given that the density (D) of the Green object is 2.0 kg/L^3 and the mass is 5 kg. Explain how you calculate the volume of the object with this information. (Hint use the water displacement method to verify your answer.)

    a) Divide the mass (M) of the object by the density (D) of the object to calculate the volume (V=M/D).*
    b) Divide the density (D) of the object by the mass (M) of the object to calculate the volume (V=D/M).
    c) Multiply the mass (M) of the object by the density (D) of the object to calculate the volume (V=MD).

8. Given that the density (D) of the Red object is 4.0 kg/L^3, and the mass (M) is 5 kg. Explain how you would calculate the mass of the object if you only had the density of the object. (Hint use the water displacement method to verify your answer.)

    a) Use the water displacement method to calculate the volume of the object. Multiply the density of the object by the volume of the object and you will have the mass of the object (M=DV).*
    b) Use the water displacement method to calculate the volume of the object. Divide the volume of the object by the density of the object and you will have the mass of the object (M=V/D).
    c) Use the water displacement method to calculate the volume of the object. Divide the density of the object by the volume of the object and you will have the mass of the object (M=D/V).

9. Given that the density of the Green object is 2kg/L^3 and the mass (M) is 5kg. Explain how you would calculate the mass of the object if you only had the density of the object. (Hint use the water displacement method to calculate the volume (V) of the object.)

    a) Use the water displacement method to calculate the volume of the object. Multiply the density of the object by the volume of the object and you will have the mass of the object (M=DV).*
    b) Use the water displacement method to calculate the volume of the object. Divide the density of the object by the volume of the object and you will have the mass of the object (M=D/V).
    c) Use the water displacement method to calculate the volume of the object. Divide the volume of the object by the density of the object and you will have the mass of the object (M=V/D).

10. Given that the density (D) of the Red object is 0.4 kg/L^3, and the mass (M) is 2 kg. Explain how you would calculate the mass of the object if you only had the density of the object. (Hint use the water displacement method to calculate the volume (V) of the object.)

    a) Use the water displacement method to calculate the volume of the object. Divide the density of the object by the volume of the object and you will have the mass of the object (M=D/V).
    b) Use the water displacement method to calculate the volume of the object. Divide the volume of the object by the density of the object and you will have the mass of the object (M=V/D).
    c) Use the water displacement method to calculate the volume of the object. Multiply the density of the object by the volume of the object and you will have the mass of the object (M=DV).*

11. Given that the density (D) of the Green object is 0.8kg/L^3 and the mass (M) is 4 kg. Explain how you would calculate the mass of the object if you only had the density of the object. (Hint use the water displacement method to calculate the volume (V) of the object.)

    a) Use the water displacement method to calculate the volume of the object. Divide the volume of the object by the density of the object and you will have the mass of the object (M=V/D).
    b) Use the water displacement method to calculate the volume of the object. Multiply the density of the object by the volume of the object and you will have the mass of the object (M=DV).*
    c) Use the water displacement method to calculate the volume of the object. Divide the density of the object by the volume of the object and you will have the mass of the object (M=D/V).

12. Given that the density (D) of the Red object is 4.0 kg/L^3 and the mass (M) of the object is 5 kg. Explain how you would calculate the density of the object if you only had the mass of the object. (Hint use the water displacement method to calculate the volume (V) of the object.)

    a) Use the water displacement method to calculate the volume of the object. Multiply the mass of the object by the volume of the object and you will have the density of the object (D=MV).
    b) Use the water displacement method to calculate the volume of the object. Divide the mass of the object by the volume of the object and you will have the density of the object (D=M/V).*
    c) Use the water displacement method to calculate the volume of the object. Divide the volume of the object by the mass of the object and you will have the density of the object (D=V/M).

13. Given that the density (D) of the Yellow object is 0.5 kg/L^3 and the mass (M) of the object is 5 kg. Explain how you would calculate the density of the object if you only had the mass of the object. (Hint use the water displacement method to calculate the volume (V) of the object.)

    a) Use the water displacement method to calculate the volume of the object. Divide the volume of the object by the mass of the object and you will have the density of the object (D=V/M).
    b) Use the water displacement method to calculate the volume of the object. Divide the mass of the object by the volume of the object and you will have the density of the object (D=M/V).*
    c) Use the water displacement method to calculate the volume of the object. Multiply the mass of the object by the volume of the object and you will have the density of the object (D=MV).

14. Given that the density (D) of the Red object is 0.4 kg/L^3 and the mass (M) of the object is 2 kg. Explain how you would calculate the density of the object if you only had the mass of the object. (Hint use the water displacement method to calculate the volume (V) of the object.)

    a) Use the water displacement method to calculate the volume of the object. Multiply the mass of the object by the volume of the object and you will have the density of the object (D=MV).
    b) Use the water displacement method to calculate the volume of the object. Divide the mass of the object by the volume of the object and you will have the density of the object (D=M/V).*
    c) Use the water displacement method to calculate the volume of the object. Divide the volume of the object by the mass of the object and you will have the density of the object (D=V/M).

15. Given that the density (D) of the Yellow object is 1.6 kg/L^3 and the mass (M) of the object is 8 kg. Explain how you would calculate the density of the object if you only had the mass of the object. (Hint use the water displacement method to calculate the volume (V) of the object.)
    a. Use the water displacement method to calculate the volume of the object. Divide the mass of the object by the volume of the object and you will have the density of the object (D=M/V).*
    b. Use the water displacement method to calculate the volume of the object. Divide the volume of the object by the mass of the object and you will have the density of the object (D=V/M).
    c. Use the water displacement method to calculate the volume of the object. Multiply the mass of the object by the volume of the object and you will have the density of the object (D=MV).

Appendix E. Table of Specifications for Pretest & Posttest

A table of specifications for both the Pretest and Posttest is presented below. Each item is identified by type (declarative knowledge based, or problem solving based). Assessments mirror each other in structure, each containing 15 items (3) declarative knowledge, and (12) problem solving). Each question is true/false based.

Pretest Table of Specifications

Pretest					
Item #	Type	Item #	Type	Item #	Type
1	Prob. Solv.	6	Prob. Solv.	11	Prob. Solv.
2	Dec. Knowl.	7	Dec. Knowl.	12	Prob. Solv.
3	Prob. Solv.	8	Prob. Solv.	13	Prob. Solv.
4	Prob. Solv.	9	Prob. Solv.	14	Prob. Solv.
5	Dec. Knowl.	10	Prob. Solv.	15	Prob. Solv.

Posttest Table of Specifications

Posttest					
Item #	Type	Item #	Type	Item #	Type
1	Prob. Solv.	6	Prob. Solv.	11	Prob. Solv.
2	Prob. Solv.	7	Prob. Solv.	12	Prob. Solv.
3	Prob. Solv.	8	Dec. Knowl.	13	Dec. Knowl.
4	Prob. Solv.	9	Dec. Knowl.	14	Prob. Solv.
5	Prob. Solv.	10	Dec. Knowl.	15	Dec. Knowl.

Appendix F. Pretest Items

1. Object A has a volume of 14 L^3 and a density of 6 kg/L^3. The mass of object A is 84 kg. (True* / False)
2. The formula used to calculate the volume of an object when you have the mass and density of the object is: (volume = density multiplied by mass) (True / False*)
3. Object C has a volume of 0.77 L^3 and a density of 0.14 kg/L^3. The mass of object C is 5.5 kg. (True / False*)
4. Object A has a mass of 15 kg and a volume of 7 L^3. The density of Object A is 105 kg/L^3. (True / False*)
5. The formula used to calculate the mass of an object when you have the density and volume of the object is: (mass = density divided by volume) (True / False*)
6. Object A has a mass of 4 kg and a density of 7 kg/L^3. The volume of object A is 28 L^3. (True / False*)
7. The formula used to calculate the density of an object when you have the mass and volume of the object is: (density = mass multiplied by volume) (True / False*)
8. Object B has a volume of 7 L^3 and a density of 21 kg/L^3. The mass of object B is 0.33 kg. (True / False*)
9. Object B has a mass of 42 kg and a density of 26 kg/L^3. The volume of object B is 0.62 L^3. (True / False*)
10. Object A has a mass of 4 kg and a density of 7 kg/L^3. The volume of object A is 0.57 L^3. (True / False*)
11. Object C has a volume of 0.13 L^3 and a mass of 0.47 kg. . The density of object C is 0.04 kg/L^3. (True / False*)
12. Object B has a volume of 33 L^3 and a mass of 27 kg. The density of Object B is 1.22 kg/L^3. (True / False*)
13. Object A has a volume of 14 L^3 and a density of 6 kg/L^3. The mass of object A is 0.43 kg. (True / False*)
14. Object C has a mass of 1.5 kg and a density of 7.3 kg/L^3. The volume of Object C is 10.95 L^3. (True / False*)
15. Object A has a mass of 15 kg and a volume of 7 L^3. The density of Object A is 2.14 kg/L^3. (True* / False)

Appendix G. Posttest Items

1. Object B has a volume of 33 L^3 and a mass of 27 kg. The density of Object B is 0.82 kg/L^3. (True* / False)
2. Object C has a volume of 0.13 L^3 and a mass of 0.47 kg. .The density of object C is 0.06 kg/L^3. (True / False*)
3. Object C has a mass of 1.5 kg and a density of 7.3 kg/L^3. The volume of object C is 4.9 L^3. (True / False*)
4. Object B has a mass of 42 kg and a density of 26 kg/L^3. The volume of object B is 1,092 L^3. (True / False*)
5. Object B has a mass of 42 kg and a density of 26 kg/L^3. The volume of object B is 1.62 L^3. (True* / False)
6. Object B has a volume of 7 L^3 and a density of 21 kg/L^3. The mass of object B is 3 kg. (True / False*)
7. Object B has a volume of 7 L^3 and a density of 21 kg/L^3. The mass of object B is 147 kg. (True* / False)
8. The formula used to calculate the volume of an object when you have the mass and density of the object is: (volume = density divided by mass) (True / False*)
9. Object C has a volume of 0.77 L^3 and a density of 0.14 kg/L^3. The mass of object C is 0.18 kg. (True / False*)
10. Object B has a volume of 33 L^3 and a mass of 27 kg. The density of Object B is 891 kg/L^3. (True / False*)
11. Object A has a mass of 4 kg and a density of 7 kg/L^3. The volume of object A is 1.75 L^3. (True / False*)
12. Object A has a volume of 14 L^3 and a density of 6 kg/L^3. The mass of object A is 2.3 kg. (True / False*)
13. The formula used to calculate the mass of an object when you have the density and volume of the object is: (mass = volume divided by density) (True / False*)
14. Object A has a mass of 15 kg and a volume of 7 L^3. The density of Object A is 0.47 kg/L^3. (True / False*)
15. The formula used to calculate the density of an object when you have the mass and volume of the object is: (density = volume divided by mass) (True / False*)

Appendix H. Informed Consent

Introduction:
The purposes of this form are to:

- Provide you with the necessary information you need to YES or NO to participation in this research study
- Record the consent of those who say YES

If you agree to participate in this study, you will are asked to click YES and then click the SUBMIT button.

Project Title:
Investigating the effect different types of self-explanation prompt and self-explanation activity have on learning outcomes when using an instructional simulation.

Researchers:
Responsible Project Investigator: Dr. Ginger Watson, Darden College of Education, gswatson@odu.edu
Investigators: Paul MacLoughlin, PhD. Candidate, Darden College of Education Mary C. Enderson, Ph.D., Darden College of Education Rich Whittecar, Ph.D., College of Sciences

Description of Research Study:
Many studies demonstrate the efficacy of using the self-explanation learning strategy to support knowledge and skill acquisition. However, few studies investigate the use of this strategy when using an instructional simulation. The iCAP (Interactive, Constructive, Active, Passive) Hypothesis holds that higher levels of learner activity will drive improved learning outcomes. Self-explanation and instructional simulations appear to be a strong fit for instructional approaches that are aligned with the iCAP framework. This study investigates the use of the self-explanation strategy within an instructional simulation, and tests iCAP Hypothesis using this instructional design model. Upon completion of the elements of this study participants will receive extra credit for their participation.

Exclusionary Criteria:
Students enrolled in science related courses such as Physics, Chemistry, or Biology should not participate in this study. The instructional content that is the focus of the study is within the Chemistry domain, and students with intermediate or advanced capability will be excluded based on performance on a pretest.

Risks & Benefits
Risks: No risks for participating in this study have been identified.

Benefits:

• Participants may acquire skills related to using the self-explanation learning strategy that can be applied across multiple domains and support ongoing learning.

• Participants may acquire knowledge related to the scientific domain of Chemistry.

New Information:

If the researchers find new information during this study that would reasonably change your decision about participating, then they will give it to you.

Confidentiality:

The researchers will take reasonable steps to keep information related to the study confidential. No personal data will be shared outside the study team (a short demographic survey is completed as a part of the study).

Withdrawal Privilege:

It is OK for you to say NO. Even if you say YES now, you are free to say NO later, and walk away or withdraw from the study -- at any time. Your decision will not affect your relationship with Old Dominion University, or otherwise cause a loss of benefits to which you might otherwise be entitled. The researchers reserve the right to withdraw your participation in this study, at any time, if they observe potential problems with your continued participation.

Compensation for Illness or Injury

If you say YES, then your consent in this document does not waive any of your legal rights. However, in the event of harm, injury, or illness arising from this study, neither Old Dominion University nor the researchers are able to give you any money, insurance coverage, free medical care, or any other compensation for such injury. In the event that you suffer injury as a result of participation in any research project, you may contact Dr. Jill Stefaniak, Chair of the Darden College of Education Human Subjects Committee, at jstefani@odu.edu or 757-683-6696, or Old Dominion University Office of Research at 757-683-3460, who will be glad to review the matter with you.

Voluntary Consent

By clicking the SUBMIT button you are saying several things. You are saying that you have read this form or have had it read to you, that you are satisfied that you understand this form, the research study, and its risks and benefits. The researchers should have answered any questions you may have had about the research. If you have any questions later on, then the researchers should be able to answer them. You may contact Dr. Ginger Watson at gswatson@odu.edu, with any questions that you may have. You may also contact Paul MacLoughlin at pmacl001@odu.edu

If at any time you feel pressured to participate, or if you have any questions about your rights or this form, then you should contact Dr. Jill Stefaniak, Chair of the Darden College of Education Human Subjects Review Committee, Old Dominion University, at jstefani@odu.edu or 757-683-6696.

And importantly, CLICKING the SUBMIT button below, you are telling the researcher YES, that you agree to participate in this study. The researcher should give you a copy of this form for your records.

Investigators Statement

I certify that I have explained to this subject the nature and purpose of this research, including benefits, risks, costs, and any experimental procedures. I have described the rights and protections afforded to human subjects and have done nothing to pressure, coerce, or falsely entice this subject into participating. I am aware of my obligations under state and federal laws, and promise compliance. I have answered the subject's questions and have encouraged him/her to ask additional questions at any time during the course of this study. I have witnessed the above signature(s) on this consent form.

Signature of Investigator:	Date:
Paul MacLoughlin	10/5/2017

Appendix I. Demographic Survey

1. Student Level:
    a. Freshman
    b. Sophomore
    c. Junior
    d. Senior
    e. Other

2. What is your major area of study? (Text Entry Field)

3. What is your current GPA? (Text Entry Field)

Appendix J. Practice Activities

Practice activities were presented to each participant before beginning the instructional module. Activities were standardized for each treatment, however, the structure of the prompts presented varied according to treatment.

1. Click the Same Volume button on the right side of the screen. Explain how much water is displaced when the Red object is placed in the water.
    a. 2 L^3*
    b. 4 L^3
    c. 6 L^3
    d. 8 L^3

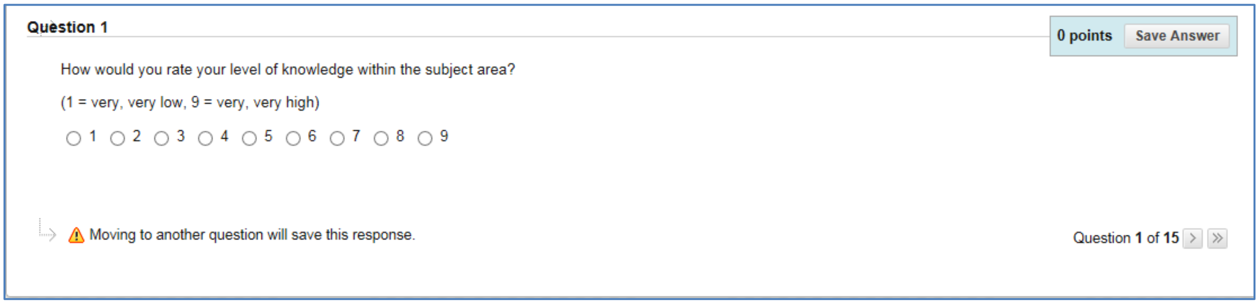
2. Click the Same Volume button on the right side of the screen. Explain how much water is displaced when the Blue object is placed in the water.
    a. 2 L^3
    b. 4 L^3
    c. 5 L^3*
    d. 8 L^3

3. Click the Same Volume button on the right side of the screen. Explain how much water is displaced when the Red object is placed in the water.
    a. 2 L^3
    b. 4 L^3
    c. 5 L^3*
    d. 8 L^3

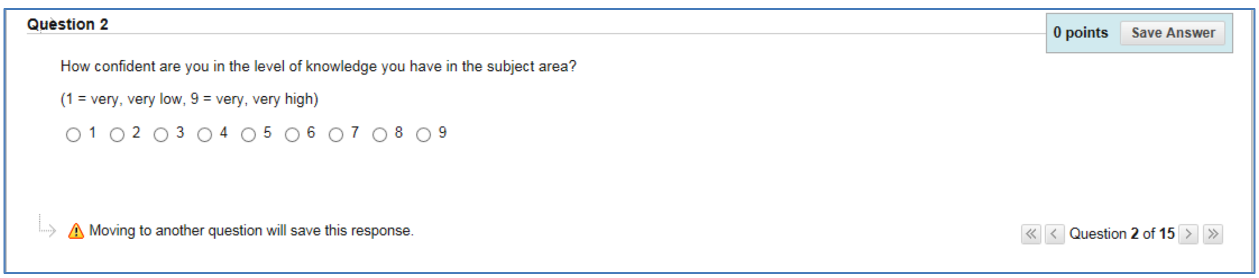
Appendix K. Measuring Self-efficacy

Self-efficacy reporting scales presented to participants in all treatments before and after the instructional module.

Self-efficacy Measurement Scale - Knowledge



Self-efficacy Measurement Scale - Confidence



Appendix L. Manipulation Check

Manipulation checks to confirm treatment assignment.

Close Prompts Treatment

QUESTION 18

I only received multiple choice prompts (closed prompts) during this activity.

○ Yes

○ No

Open-Prompts Treatment

Question 18

I only received text entry prompts (open prompts) during this activity.

○ Yes

○ No

No-overt Treatment

Question 18

I only received prompts that required me to generate self-explanations during this activity. I did not have to select multiple choice options or enter text when responding.

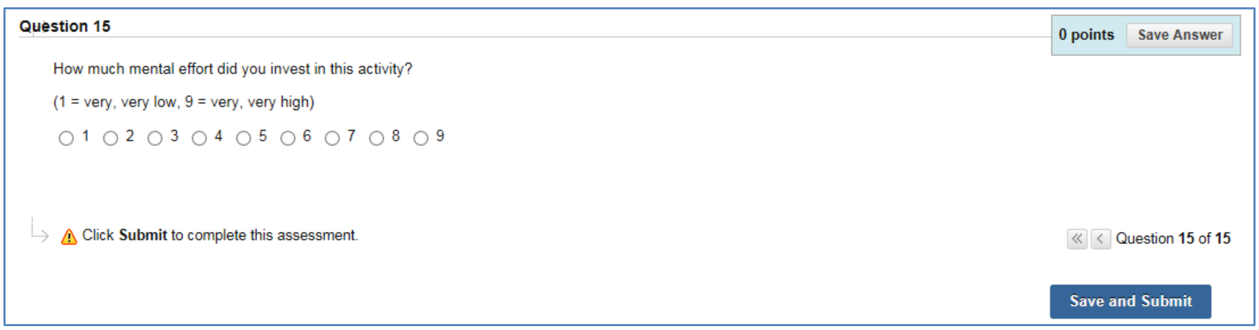
○ Yes

○ No

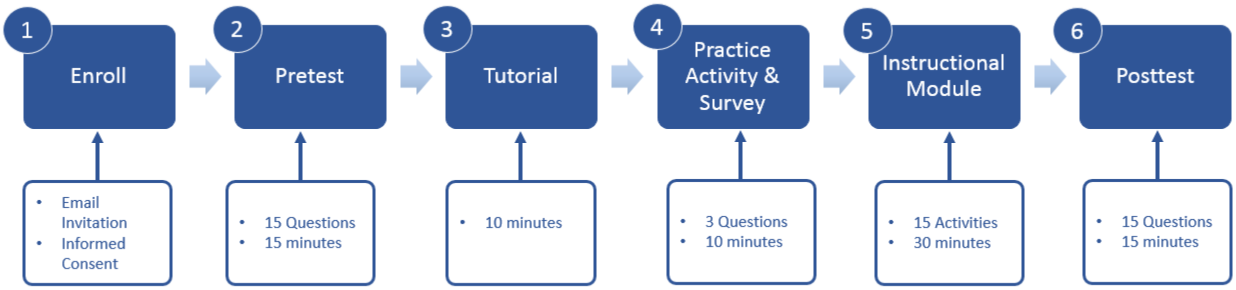
Appendix M. Measuring Cognitive Load

Cognitive Load Measurement Scale – Domain Complexity

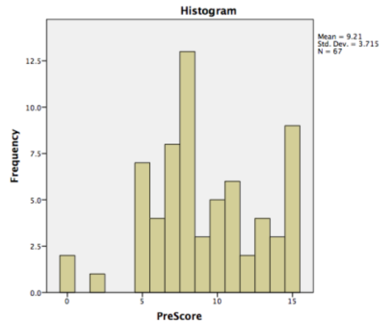
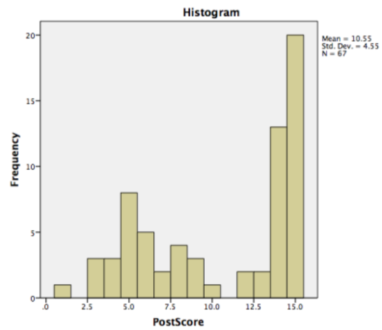
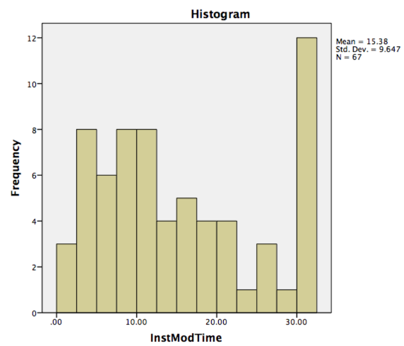
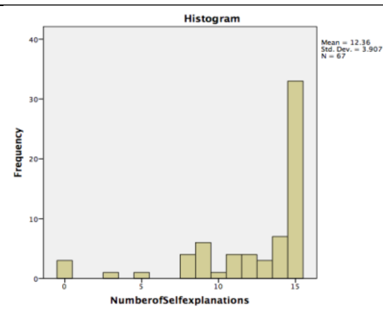
Cognitive Load Measurement Scale – Mental Effort

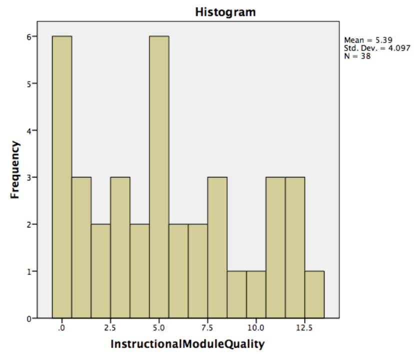
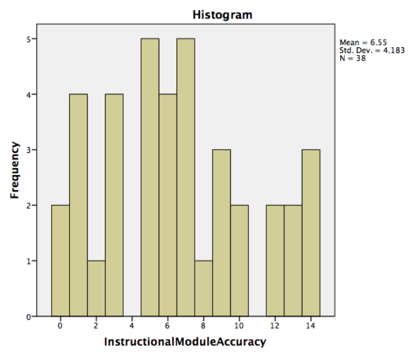
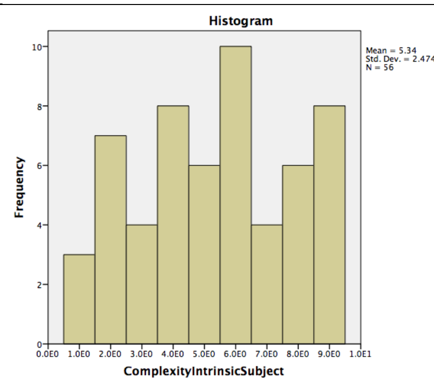
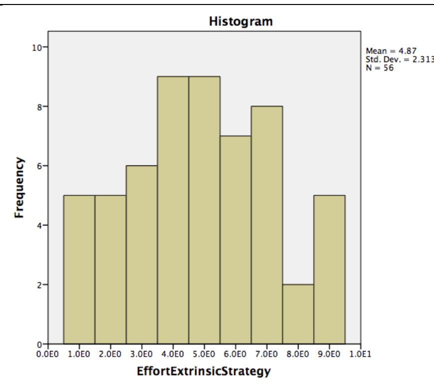


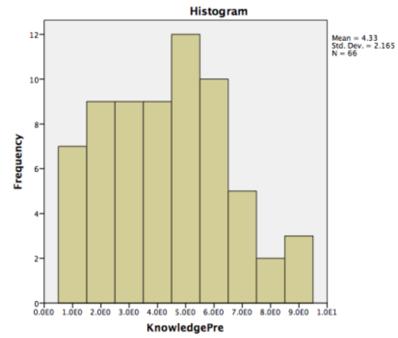
Appendix N. Study Procedure



Appendix O. Histograms

<table>
<tr><th>Variable</th><th>Histogram</th></tr>
<tr><td>Pretest Score</td><td>
</td></tr>
<tr><td>Posttest Score</td><td>
</td></tr>
<tr><td>Instructional Module Time</td><td>
</td></tr>
<tr><td>Quantity of Self-explanations</td><td>
</td></tr>
</table>

Quality of Self-explanations	
Accuracy of Self-explanations	
Intrinsic Cognitive Load	
Extraneous Cognitive Load	

<table>
<tr><td>Self-efficacy Knowledge Pre-instruction</td><td>
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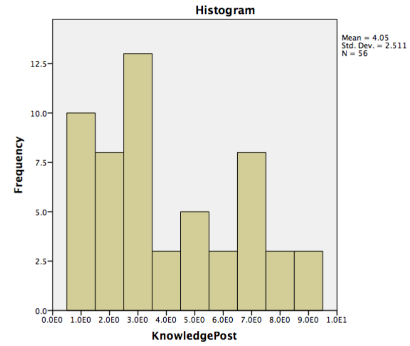
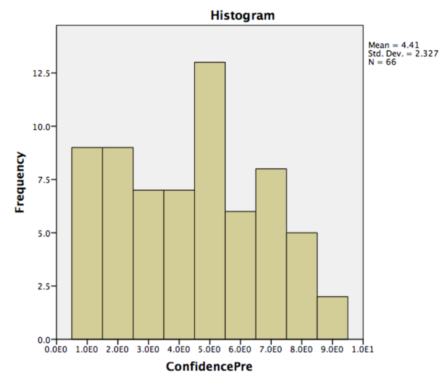
<tr><td>Self-efficacy Knowledge Post-instruction</td><td>
</td></tr>
<tr><td>Self-efficacy Confidence Pre-instruction</td><td>
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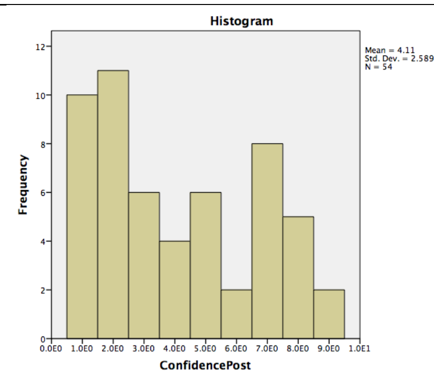
<tr><td>Self-efficacy Confidence Post-instruction</td><td>
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</table>

Appendix P. Test for Normalcy of Data

Kolmogorov-Smirnov and Shapiro-Wilk tests

	Kolmogorov-Smirnov			Shapiro-Wilk		
Variable	Statistic	df	Sig	Statistic	df	Sig
PreScore	0.150	67	0.001**	0.946	67	0.006**
PostScore	0.268	67	0.000***	0.823	67	0.000***
KnowledgePre	0.110	66	0.047*	0.954	66	0.015*
KnowledgePost	0.216	56	0.000***	0.900	56	0.000***
ConfidencePre	0.122	66	0.015*	0.942	66	0.004**
ConfidencePost	0.181	54	0.000***	0.894	54	0.000***
Complexity	0.109	56	0.095	0.938	56	0.006**
Effort	0.094	56	0.200	0.955	56	0.037*
InstModTime	0.139	67	0.003**	0.904	67	0.000***
InstModAccuracy	0.115	38	0.200	0.948	38	0.076
InstModQuality	0.117	38	0.200	0.929	38	0.018*
InstModNofSE	0.260	67	0.000***	0.715	67	0.000***

*** $p < 0.001$

** $p < 0.01$

* $p < 0.05$

VITA

Paul Michael MacLoughlin
917 Hillcrest Ct. Tallahassee FL. 32308

OVERVIEW

Results-oriented Human Resource Development professional experienced in the development, delivery, and evaluation of effective solutions to optimize executive, manager and employee performance for globally dispersed workforces. Professional experience gained across a variety of industries, including insurance, financial services, technology, oilfield services, and higher education.

EXPERTISE

Executive, Manager, and Workforce Development, Performance Consulting, Measurement & Evaluation

EXPERIENCE

Program Manager | Liberty Mutual
11/2015 – Present

- Manage global leadership development programs centered around experiential learning and executive exposure
- Consult with executive teams from business units and corporate departments to ensure alignment of leadership development programs with organizational initiatives and business objectives
- Identify and assess trends in leadership and managerial practices to drive individual and organizational performance
- Manage data collection, analysis and reporting processes to evaluate leadership, management, and professional development programs
- Develop and deliver progress reports and annual analysis to executive teams for global development initiatives
- Manage data collection, analysis and reporting for operations metrics and provide recommendations to support ongoing management decisions and strategic planning

Sr. Instructional Designer | Liberty Mutual
05/2011 – 11/2015

- Design and develop comprehensive leadership development programs for Managers, Senior Managers, and Executives
- Monitor developments and make recommendations related to instructional technologies to enable the continuous improvement of training and development practices within the organization
- Develop training and assessment programs for Core Management Curriculum
- Manage multiple learning technologies supporting organization-wide training initiatives

EDUCATION

M.S. Training and Organization Development
University of Houston
Graduated 2004, GPA 3.7

Ph.D. Student in Instructional Design and Technology
Title: “Investigating Application of the Self-explanation Learning Strategy During an Instructional Simulation”
Old Dominion University
Graduation Date: 05/2018