Self-Regulated Learning in Virtual Simulations

by

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ABSTRACT

Virtual simulations allow trainees to practice on their own. To effectively practice on their own, trainees should be able to self-regulate their learning. Even though there are claims that virtual simulations can foster self-regulated learning processes, there is no evidence to conclude that trainees are able to self-regulate their learning within these types of simulations as described within popular models of self-regulated learning (i.e., Zimmerman 2000, 2002, 2011; Pintrich, 2000, 2004). If trainees are not self-regulating their learning as specified by these models, it causes concern for the effectiveness of allowing trainees to practice on their own within virtual simulations. This study examined two questions: (a) Do learners self-regulate their learning within virtual simulations in accordance with the accepted models of self-regulated learning and (b) what model of self-regulated learning best fits the flow of self-regulated learning processes exhibited by the learners?

The results indicated the following. First, participants self-regulated their learning. In other words, participants learned how to execute the tasks in the virtual simulation more efficiently and quickly, participants exhibited all of the self-regulated learning processes, and their learning was related to exhibiting these processes. Second, participants did not exhibit the self-regulated learning

processes in the cyclical flow described by Zimmerman. Therefore, it seemed like the nature of self-regulation was dependent on the task. Taken together, these results provided some preliminary support that virtual simulations can be supplied to trainees for the purpose of self-learning.

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CHAPTER I. INTRODUCTION

The Department of Defense (DoD) must train US soldiers to have the knowledge and skills that will be used in situations related to defense and national security. There are, however, an unlimited number of situations to train for that range in both stress and complexity (Fletcher, 2009). Many of those situations are not readily available or are too dangerous to experience in real life (Mantovani, 2001). Therefore, the DoD often uses simulations to train soldiers for these complex and stressful situations (Fletcher, 2009).

The DOD defines a simulation as the implementation of a model, which represents a system, process, entity or phenomenon, in order to show how it operates over time (DoD, 1998). The DoD classifies simulations into three types: live, virtual, and constructive (DoD, 1998). A live simulation illustrates a model by means of real people using real equipment within a collocated environment. A virtual simulation illustrates a model by means of fabricated equipment, people, environments, or some combination thereof. A constructive simulation illustrates a mathematical, decision-making, or statistical model of a system by which people input conditions into the model and the system simulates the outcome.

Of the three types of simulations, virtual simulations (i.e., especially those that resemble games or other virtual environments) have received much attention (Fletcher, 2009) due to their ability to make training more accessible, including the ability to train on one's own during free time. Albeit convenient, training on one's own relies on motivational and cognitive processes that differ from those employed when training with instructors.

Self-Regulated Learning

Training on one's own has been primarily researched within the education domain. Specifically, education researchers refer to the processes that occur during this type of learning as self-regulated learning, which is defined as the "processes whereby learners personally activate and sustain cognitions, affects, and behaviors that are systematically oriented toward the attainment of personal goals" (Zimmerman & Schunk, 2011). During self-regulated learning, learners attempt to reduce the discrepancy between their learning goals and their current learning performance by adapting their cognitions, affects, and behaviors to the requirements of the learning task.

Models of self-regulated learning. There is no single model of self-regulated learning. Rather there are multiple models that stem from various learning theories. The most common models of self-regulated learning arose

from social cognitive theory (Pintrich, 2000, 2004; Schunk, 2001; Schunk & Usher, 2011; Zimmerman, 2000) and information processing theory (Winne 2001; Winne & Hadwin, 1998, 2008). Despite originating from different learning paradigms, models of self-regulated learning overlap substantially (Wolters, 2010).

Therefore, the following discussion will involve only the most predominant models of self-regulated learning, which were both derived from social cognitive theory.

Zimmerman (2000, 2002, 2011) and Pintrich (2000, 2004) developed the two most commonly cited models of self-regulated learning. Those two models describe similar types of processes. However, these two models describe different ways in which these processes are organized (i.e. orders in which these processes are exhibited). Following is a discussion of the different types of self-regulated learning processes and the theoretical ways these processes are organized.

Self-regulated learning processes. The Zimmerman (2000, 2002, 2011) and Pintrich (2000, 2004) models contain similar phases and processes. Table 1 shows a combination of the processes described by both theorists. The three over-arching self-regulated learning phases (hereafter referred to as macro processes) discussed by both theorists are forethought, performance, and self-

reflection. Contained within each phase are individual processes (hereafter referred to as micro processes).

Table 1

Self-regulated learning processes combined from Zimmerman (2000, 2002, 2011) and Pintrich (2000, 2004)

Forethought	Performance	Self-reflection
Task Analysis	Monitoring	Self-Judgment
Perceptions of Task & Context	Metacognitive monitoring	Self-evaluation
Goal Setting	Monitoring of Motivation and Affect	Causal Attribution
Assessing Prior Knowledge	Monitoring of Performance and Progress	Self-Reaction
Assessing Metacognitive Knowledge	Self-observation of behavior	Affect / Self-satisfaction
Strategy Planning	Self-questioning	Adaptive or Defensive Reactions
Self-Motivation Beliefs	Control	
General motivation	Strategy Selection and Adaptation	
Self-efficacy	Resource Allocation	
Outcome Expectations	Increase or Decrease Effort	
Task Interest	Increase or Decrease Persistence	
Goal Orientation	Seeking Help	
Task Value		

Forethought phase. In the forethought phase, learners engage in two micro processes: task analysis and self-motivation belief assessment. During task analysis, learners assess the learning task and its context and then set goals to

accomplish the learning task. Following goal setting, learners plan strategies to accomplish their goals. Strategies include ways to guide cognition, affect, and behavioral execution (Pressley & Woloshyn, 1995; Zimmerman, 2011). During self-motivation belief assessment, learners assess their motivation to initiate their identified strategies (Zimmerman, 2011). Motivation affects one's drive to complete the planned strategies. High motivation is believed to result from a combination of having high self-efficacy, an expectation that the learner's behaviors will produce a positive outcome, an interest in the learning task, a perceived value in completing the learning task, and an interest in mastering the learning task (Zimmerman, 2011).

Performance phase. The performance phase consists of two micro processes: monitoring and control (Pintrich, 2000, 2004; Zimmerman, 2000, 2002, 2011). Monitoring refers to the learners' efforts to maintain awareness of their motivation, cognitive processes, and progress toward their goal achievement (Pintrich, 2000, 2004; Wolters, 2010; Zimmerman, 2000, 2010). Control refers to the management and modification of the motivation, cognitive processes, and strategies used to achieve their goals.

Self-reflection phase. In the self-reflection phase, learners engage in two micro processes: self-judgment and self-reaction (Zimmerman, 2011). When

making self-judgments, learners evaluate their performance against an internal standard, and then attribute the success or failure of their performance to themselves or an uncontrollable cause. Learners self-react to their performance in two ways. First, learners assess how satisfied they are with their performance. The extent to which the learner is satisfied with their performance produces a negative to positive affective reaction. Second, learners combine their causal attributions and their self-satisfaction and adopt either an adaptive or defensive inference, which are conclusions that learners make about either altering their future approaches or not altering their approaches, respectively.

Organization of self-regulated learning. As discussed, Zimmerman's (2000, 2002, 2011) model and Pintrich's (2000, 2004) model agree about the overall types of self-regulated learning processes. They disagree, however, about the organization of those processes. Zimmerman (2000, 2002, 2011) stressed that self-regulated learning is cyclical. Specifically, learners will first engage in forethought when they begin a task, then performance while they attempt to complete the task, and lastly self-reflection after they completed the task. The learners' self-reflections will then affect future forethought, thus continuing the cycle. In contrast, Pintrich (2000, 2004) asserted that self-regulated learning is

not inherently cyclical. Instead, learners will exhibit self-regulated learning in a flexible and non-linear order that is adapted to the learning task at hand.

Self-regulated learning and virtual simulations. It has been suggested that virtual simulations can foster self-regulated learning (Cannon-Bowers & Bowers, 2010; Zap & Code, 2009). Despite these claims, only three studies have assessed whether learners self-regulated their learning within virtual simulations. First, Ford, Smith, Weissbein, Gully, and Salas (1998) assessed the relationship among goal orientation, metacognitive activity, practice strategies, and performance outcomes within the virtual simulation, TANDEM. Second, Orvis, Horn, and Belanich (2006) assessed factors such as motivation, self-efficacy, goal orientation, and metacognitive activity in relation to performance within the virtual simulation, America's Army. Third, Nietfeld, Hoffman, McQuiggan, and Lester (2008) assessed the effects of goal orientation and metacognitive monitoring on performance within the virtual simulation, Crystal Island.

Table 2

Self-regulated learning processes evaluated within PC-based virtual simulations

Forethought	Performance	Self-reflection
Task Analysis	Monitoring	Self-Judgment
Perceptions of Task & Context	<u>Metacognitive monitoring</u> ^{1, 2}	Self-evaluation
Goal Setting	Monitoring of Motivation and Affect	Causal Attribution
Assessing Prior Knowledge	<u>Monitoring of Performance and Progress</u> ^{1, 2, 3}	Self-Reaction
Assessing Metacognitive Knowledge	Self-observation of behavior	<u>Affect / Self-satisfaction</u> ²
Strategy Planning	Self-questioning	Adaptive or Defensive Reactions
Self-Motivation Beliefs	Control	
<u>General motivation</u> ²	<u>Strategy Selection and Adaptation</u> ^{1, 2}	
<u>Self-efficacy</u> ^{1, 2}	Resource Allocation	
Outcome Expectations	Increase or Decrease Effort	
<u>Task Interest</u> ³	Increase or Decrease Persistence	
<u>Goal Orientation</u> ^{1, 2, 3}	Seeking Help	
Task Value		

Note. The underlined processes were measured within a PC-based virtual simulation

¹ Ford et al. (1998), ² Orvis, Horn, & Belanich (2006), ³ Nietfeld, Hoffman, McQuiggan, and Lester (2008)

Without dispute, Ford et al. (1998), Orvis, et al. (2006), and Nietfeld, et al. (2008) shed light on self-regulated learning within virtual simulations. As shown in Table 2, however, none of those studies measured all of the self-regulated learning processes described by Zimmerman (2000, 2002, 2011) and Pintrich (2000, 2004) within a virtual simulation. That is problematic. Training on one's own should be most successful when learners exhibit self-regulated learning processes. For example, in academic learning environments, students who exhibit

self-regulated learning processes tend to exhibit greater academic achievement (i.e., learning, grades) than students who do not exhibit these processes (e.g., Pintrich & DeGroot, 1990, Wolters & Pintrich, 1998; Zimmerman & Martinez-Pons, 1990).

Purposes of Current Study

The primary purpose of the current study was to assess whether learners who were using a virtual simulation self-regulated their learning in accordance with Zimmerman's (2000, 2002, 2011) and Pintrich's (2000, 2004) models. To conclude that learners did so, there had to be evidence that a) learning took place, b) all six of the micro self-regulated learning models were active at least once during the task, and c) learning was related to changes in self-regulated learning processes.

The secondary purpose of the present study was to assess which model best described the structure of learners' self-regulated learning processes. To conclude that Zimmerman's model of self-regulated learning best fit that structure, there had to be evidence that the flow between self-regulated learning phases was cyclical (Zimmerman, 2000, 2002, 2011). Otherwise, it would be concluded that Pintrich's (2000, 2004) model best fit the structure of learners' self-regulated learning processes.

As such, the current study was the first to determine whether learners who were using a virtual simulation self-regulated their learning in accordance with the most accepted models of that type of learning. Additionally, the current study was the first to determine which of those models best described the structure of those learners' self-regulated learning processes. In doing so, the current research allowed us to better understand whether trainees are getting the most out of training on their own in virtual simulations.

CHAPTER II. METHOD

Participants

The participants were 76 Texas Tech University students. They reported having normal or corrected-to-normal vision and no prior experience playing Portal, the virtual simulation used in this study. Each received \$20 for participating.

Of the 76 students, only 65 were included in the data analysis. Of the eleven students who were not included in the data analysis, eight participants ran out of time or elected to quit, whereas three participants were omitted for reasons related to data collection errors.

Apparatus and Materials

Testing environment. The participant was seated within the participant partition and used an Apple iMac, which had a 27-inch display, a 2.66 GHz Intel Core i5 processor, 4 GB of RAM, and a microphone (Figure 1, Panel a). The experimenter was seated within the experimenter partition and viewed the participants' activity via a 24" Apple LED Cinema Display that was connected to the participant's iMac (Figure 1, Panel b). The experimenter transcribed the

participants' verbalizations using an Apple MacBook Pro, which had a 15-inch display, a 2.66 GHz Intel Core i7 processor, and 4 GB of RAM.

Figure 1. (A) Participant partition and (B) experimenter partition with respective hardware.

Virtual simulation. During the study, participants interacted with the virtual simulation Portal, which is a single-player video game released by Valve Software. In Portal, players use a mouse and keyboard to navigate a character through a three-dimensional environment and solve a series of puzzles. It is necessary to solve these puzzles in order to complete each level.

Portal was chosen for two reasons. First, Portal afforded opportunities for players to set goals (e.g., reach the next elevator on a platform), define strategies (e.g., plan to shoot a portal on the wall over the platform), execute a combination of skills involved in a given strategy (e.g., shoot a portal over the platform and

shoot a portal on an accessible wall), monitor the success of the strategies (e.g., determine whether the player reached the elevator), and make corrective changes to the strategies (e.g., develop a different strategy if necessary). These processes are found within the Zimmerman (2000, 2002, 2011) and Pintrich (2000, 2004) models of self-regulated learning. Second, Portal does not give the participant any external feedback about their performance. For example, there is no indication of time remaining or elapsed, points earned, or lives left. This afforded an opportunity for participants to self-regulate, or rely on internal feedback loops rather than external feedback.

Data collection software. Guerilla Silverback was used to record and integrate the participants' game play, mouse clicks, and audio (Clearleft Software). RUI was used to log all participant mouse and keyboard activity (Kukreja, Stevenson, & Ritter, 2006). Performance metrics were extracted from video of the participants' game play and RUI's log files.

Procedure

Participants were tested individually. Each testing session had four stages: setup, game-play, debriefing, and data preparation.

Setup. At the beginning of the set-up stage, participants completed a demographic questionnaire, completed the Mental Rotation Test (MRT), and then

learned the rules of the study. Following, participants practiced the think-aloud protocol.

To do so, participants thought aloud while they played two levels of Angry Birds within the Google Chrome browser. Angry Birds was chosen because the game presented a puzzle that required participants to set a goal (e.g., eliminate the green pigs), define strategies (e.g., determine the appropriate projection of the bird), implement their strategy, monitor their implementation, and make changes to strategies as needed. These processes are included in the Zimmerman (2000, 2002, 2011) and Pintrich (2000, 2004) models of self-regulated learning and were similar to the puzzle-solving activities required for Portal.

Finally, the experimenter began all recording (i.e., video & audio) using Guerilla Silverback and logging (i.e., keystrokes & mouse clicks) using RUI. Participants were made aware that their activity and voice were being recorded and logged.

Game-play. During the game-play stage, participants played the levels of Portal in the order in which they were structured in the game while talking out loud about what they were doing and thinking. Participants were given two hours to complete the first 12 levels (i.e., Levels 0 through 11). As the participants

talked, the primary researcher transcribed and time-stamped their verbalizations in real-time.

Debriefing. Following the game-play stage, participants were debriefed and asked whether they had any questions. After all questions were answered, participants received \$20 and were free to leave.

Data preparation. Following the debriefing, a researcher listened to the audio recording of the participant while reading through the transcript. At this time, corrections to the transcript were made.

Measures

Demographic questionnaire. Participants reported their age, gender, video game experience, and whether they had ever played Portal. Regarding video game experience, participants reported their experience on a 5-point scale where "0" indicated never and "5" indicated very frequently. Video game experience was assessed for the following game genres: (1) first-person-perspective, (2) flight simulators, (3) massively multiplayer online games, (4) sports/racing, (5) military command/strategy, (6) fighting, (7) fantasy, (8) puzzles, (9) social networking games, and (10) mobile device games.

Mental Rotation Test (MRT). Portal involves spatial navigation, so participants' spatial abilities could have impacted their performance. To account

for that possibility, participants' spatial abilities were measured with the Mental Rotation Test (MRT; Vandenberg, 1971; Vandenberg & Kuse, 1978). The MRT was chosen because it is a frequently used test of spatial ability (Mohler, 2006) with high reliability (Vandenberg & Kuse, 1978) and validity (Zimowski & Wothke, 1986).

The MRT consists of 20 items containing one reference block configuration and four candidate block configurations (See Figure 2). Two candidates are rotated versions of the reference block. The remaining two candidates are rotated mirror images of the reference block configuration, which serve as distractors. Participants' task is to correctly identify both of the candidates that are simply rotated versions of the reference (i.e., matches). Participants receive one point for every correctly identified pair for a maximum of 20 points. Conversely, participants receive no points if any of the four candidates are incorrectly chosen.

Figure 2. Two sample items from the Mental Rotation Test (MRT; Vandenberg & Kuse, 1978)

Performance variables. Two performance variables were collected from the participants' game-play: (1) the amount of time it took for a participant to complete each level and (2) the number of portals it took for a participant to complete each level. The amount of time that it took to complete a level was extracted from the videos of participant game play, which were captured by Guerilla Silverback. Specifically, the primary researcher recorded the time that indicated the start of a level (i.e., when the elevator door first opened) and the time that indicated the end of a level (i.e., when the participant entered the next elevator). The duration of each level was calculated by subtracting the start time from the end time. The number of portals shot during a level was extracted from the log file captured by RUI, which contained a time-stamped register of every mouse click and keystroke made during game-play. Because the left mouse

button was only used for shooting portals, the number of left mouse clicks was totaled for each level.

The amount of time and the number of portals that it took to complete a level captured performance during a given level. To examine learning, it was necessary to compare performance across levels. There was concern, however, that such a comparison could be confounded by the requirements of the levels. Specifically, if completing each level required a different amount of time and number of portals, then a decrease in the amount of time or the number of portals across levels could be attributed to the individual nature of the levels rather than learning. Thus, it was important to understand whether the levels used in this experiment are typically completed in the same amount of time and with the same number of portals.

Unfortunately, Valve Software does not publish data about how much time is typically taken or how many portals are typically shot to complete each level in Portal. Therefore, it was necessary to generate that data. To do so, videos from an online forum, *Portal Walkthroughs*, were used. In these videos, game players demonstrated how to solve the puzzles within Portal. From the videos, the time to complete each level was recorded using the same method previously discussed (i.e., subtracting the beginning time from the end time for each level).

The number of portals to complete each level was extracted by manually counting how many portals were shot during each level. Table 6 displays these values.

As shown in Table 3, Levels 1 through 11 were typically completed in various amounts of time and with various numbers of portals shot. Therefore, it would be incorrect to assume that a decrease in completion time or number of portals shot across levels reflected learning. Rather, such decreases across levels could also reflect the requirements of the levels that were employed in this experiment.

Table 3

The typical amounts of time and numbers of portals shot to complete levels of Portal (Portal Walkthroughs, 2011)

Level	Time	Portals
1	0:00:47	0
2	0:01:01	1
3	0:00:43	2
4	0:00:32	1
5	0:00:57	5
6	0:00:41	1
7	0:00:56	2
8	0:01:33	4
9	0:01:04	3
10	0:01:34	4
11	0:02:46	5

To avoid that potential confound, completion time and number of portals shot were converted into percentages. To do so, participants' actual performance for a given level was compared against the typical performance for that level.

Accordingly, performance was standardized. Given this correction, a reduction in percent error could be attributed to improved performance and not to the requirements of different levels. Percent error for each performance metric will hereafter be referred to as $\text{error}_{\text{time}}$ and $\text{error}_{\text{portals}}$.

$$\text{Error}_{\text{time}} = \frac{|\text{completion time} - \text{typical time}|}{\text{typical time}} \times 100$$

$$\text{Error}_{\text{portals}} = \frac{|\text{\# of portals} - \text{typical \# of portals}|}{\text{typical \# of portals}} \times 100$$

Figure 3. Percent error calculations for completion time and number of portals.

Self-regulated learning variables. As described in the procedure, participants talked out loud about what they were doing and what they were thinking. To derive meaning from what participants said, their verbalizations had to be coded as being one of the six self-regulated learning micro processes.

Coding. Coding was necessary to determine what self-regulated learning processes were verbalized while participants played Portal. The coding procedure consisted of (a) defining a coding scheme, (b) separating the transcript into segments, (c) training an associate researcher to code, and (d) coding the segments.

Coding scheme. The coding scheme consisted of Zimmerman's (2000, 2002, 2011) and Pintrich's (2004, 2000) self-regulated learning models. Specifically, the coding scheme included the 6 micro-level processes: task analysis, self-motivation beliefs, monitoring, control, self-judgment, and self-reaction. Examples of this coding scheme are included in Table 4.

Table 4

Examples of coding scheme

Micro Process	Example
Task Analysis	<i>"The elevator is across the room"</i>
Self-Motivation Beliefs	<i>"I want to get onto that platform"</i>
Monitor	<i>"I don't understand how to do this"</i>
Control	<i>"I shot a portal there"</i>
Self-Judgment	<i>"I didn't do very well"</i>
Self-Reaction	<i>"I'm pleased with how I did"</i>

Segmenting verbalizations. Next, the researcher separated the transcript of verbalizations into segments, which were defined as a single unit of thought (Jones, Farris, Elgin, Anders, & Johnson, 2005) consisting of an independent clause. Each unit of thought was listed within a Microsoft Excel spreadsheet.

One-time coder training. To ensure reliability, two researchers had to code each segment. This required the primary researcher to train an associate researcher. Training consisted of an educational and a practice component. First, the primary researcher instructed the associate researcher about self-regulated

learning, including the micro processes within the coding scheme. Second, the associate researcher practiced coding using data collected from a pilot study. Specifically, the associate researcher categorized all of the segments as being one of the 6 micro processes or as being miscellaneous. A miscellaneous segment described a verbalization that could not be categorized as one of the 6 micro-level processes.

Independent coding. Both researchers coded each segment from the present study. They employed the same procedures that were practiced during the coding training session.

CHAPTER III.

RESULTS & DISCUSSION

The results are organized in the following manner. First, analyses are presented that determined whether participants self-regulated their learning. Second, analyses are presented that determined what model of self-regulated learning best described the structure of the participants' self-regulated learning processes. Third, analyses are presented that determined whether attrition impacted the results regarding self-regulated learning.

Did Participants Self-Regulate their Learning?

Three requirements were examined to determine whether participants self-regulated their learning in ways that were consistent with Zimmerman's (2000, 2002, 2011) and Pintrich's (2000, 2004) models. Specifically, the data were examined to determine whether 1) learning took place, 2) all six micro self-regulated learning processes were active at least once during the task, and 3) learning was related to changes in self-regulated learning processes. The following analyses determined whether those requirements were met.

Requirement #1: learning. The first requirement was that learning took place. If so, then performance should have improved from the beginning of the study to the end of the study.

Dependent variables. As discussed in the Method, performance was described in terms of the error_{portals} and error_{time} per level. Better performance equated to less error. To compare performance at the beginning of the study to performance at the end of the study, variables representing the average error_{portals} and error_{time} in the beginning (i.e., Levels 3-6) and the end (i.e., Levels 8-11) of the study were calculated.

Levels 3 through 6 and 8 through 11 were chosen to represent the beginning and end of the study, respectively, for two reasons. First, Level 3 was chosen as the first level because it was the first level where the participant had access to the portal gun for the entire duration of the level. Second, the first four levels and the last four levels were included in the analysis to use the majority of the data that was collected.

Outlier analysis. Figure 4 depicts the distribution of average error_{portals} and average error_{time} for the beginning and end of the study. As seen in the figure, each performance variable contains a small number of data points that were potential outliers. Accordingly, an outlier analysis was conducted on average error_{portals} and average error_{time} for the beginning and end of the study.

(a) average error_{portals}

(b) average error_{time}

Figure 4. Distribution of (a) average error_{portals} and (b) average error_{time} for the beginning (i.e., Levels 3-6) and the end (i.e., Levels 8-11) of the study. The vertical line in the body of the graph indicates the criterion for an outlier.

An outlier was defined as any average error_{portals} and average error_{time} value that had a modified z-score greater than 3.5 (Iglewicz & Hoaglin, 1993). Average error_{portals} for the beginning of the study contained two outliers and average error_{portals} for the end of the study contained five outliers. Average error_{time} for the beginning of the study contained two outliers and average error_{time} for the end of the study contained three outliers. These outliers were replaced with the highest value that was not an outlier in their respective data sets. This approach reduced the impact of each outlier, but did not unnecessarily reduce the variance or result in missing data (Tabachnick & Fidell, 1989).

Before closing, it would be prudent to explain why the outlier analyses were conducted on average error_{portals} and average error_{time} rather than the raw data that fed into those variables (i.e., error_{portals} & error_{time} per level). When the raw data were subjected to outlier analyses, a large number of outliers were identified. If each outlier had been modified, then doing so could have substantially changed the overall nature of the performance data, which was undesirable. Furthermore, the calculation of average error_{portals} and error_{time} naturally dampened many of the extreme raw data points. As such, it was

decided to conduct the outlier analysis on average error_{portals} and average error_{time} as opposed to the raw data that fed into those calculations.

Analytic approach. Two sets of analyses were conducted. The following describes the purpose and exact nature of each set of analyses.

The first set of analyses explored whether participants' spatial abilities significantly correlated with their performance, which was possible given that Portal required spatial navigation. To do so, participants' MRT scores were correlated with average error_{portals} at the beginning and end of the study as well as average error_{time} at the beginning and end of the study. If MRT scores significantly correlated with these error variables, then subsequent analyses must account for MRT. Given that multiple correlations were significance tested, it was necessary to control for inflation of the Type I error rate. To do so, the correlations concerning average error_{portals} and average error_{time} were deemed a family, and the Bonferroni adjustment was employed to maintain a family-wise error rate of .05. Accordingly, each correlation was evaluated at the $.05/4 = .01$ level.

The second set of analyses explored whether learning occurred. To do so, participants' performance at the beginning of the study (i.e., Levels 3-6) was compared to their performance at the end of the study (i.e., Levels 8-11) for

average error_{portals} and average error_{time}. If MRT was significantly correlated with performance, then the homogeneity-of-regression (slopes) assumption would be tested as a prerequisite of the ANCOVAs. If non-significant, then repeated measures ANCOVAs with MRT as the covariate would be conducted (Huitema, 1980). Otherwise, these comparisons would involve two paired-samples t-tests. In either case, multiple comparisons would be significance tested, so it was necessary to control for inflation of Type I error rate. To do so, the comparisons concerning average error_{portals} and average error_{time} were deemed a family, and the Bonferroni adjustment was employed to maintain a family-wise error rate of .05. If two ANCOVAs were conducted, then each comparison would have been evaluated at the $.05/3 = .017$ level. If two t-tests were conducted, then each comparison would have been evaluated at the $.05/2 = .025$ level.

Outcome. The first set of analyses indicated that MRT was significantly correlated with average error_{portals} at the end of the study ($r = -0.44, p < .001$) as well as with the average error_{time} at the beginning ($r = -0.38, p < .01$) and end of the study ($r = -0.42, p < .001$). However, MRT was not significantly correlated with average error_{portals} at the beginning of the study ($r = -0.25, p = .05$). This suggested that participants' spatial abilities may have influenced at least some of their performance. Accordingly, the second set of analyses employed ANCOVAs.

The second set of analyses indicated the following about average error_{portals} and average error_{time}. First, the homogeneity-of-regression (slopes) assumption indicated that the relationship between MRT and average error_{portals} did not differ significantly as a function of when the data was collected (i.e., beginning of the study vs. end of the study), $F(1,63) = 3.82, p = .23$. In addition, the ANCOVA was significant, $F(1,63) = 14.09, p < .001$. That is, average error_{portals} was significantly greater in the beginning of the study ($M = 1096.27\%$, $SD = 1128.73\%$) than in the end of the study ($M = 424.80\%$, $SD = 338.11\%$) while accounting for MRT as a covariate. Second, the homogeneity-of-regression (slopes) assumption indicated that the relationship between MRT and average error_{time} also did not differ significantly as a function of when the data was collected (i.e., beginning of the study vs. end of the study), $F(1,63) = 3.82, p = .06$. In addition, the ANCOVA was significant, $F(1,63) = 17.10, p < .001$. That is, average error_{time} was significantly greater in the beginning of the study ($M = 308.00\%$, $SD = 276.66\%$) than in the end of the study ($M = 178.99\%$, $SD = 133.68\%$) while accounting for MRT as a covariate. Taken together, the results from these ANCOVAs suggested that participants learned how to play more efficiently (i.e., they reduced average error_{portals}) and quickly (i.e., they reduced average error_{time}) from the beginning to the end of the study. As such, these

results sufficed the first requirement of finding evidence of self-regulated learning.

Requirement #2: self-regulated learning processes. The second requirement of self-regulated learning was that participants had to exhibit each of the six self-regulated learning micro processes, as defined by Zimmerman's (2000, 2002, 2011) and Pintrich's (2000, 2004) models, at least once during the study. Following are analyses that investigated this.

Inter-rater reliability. As discussed in the Method, two researchers coded the participants' segmented verbalizations as being one of the six self-regulated learning micro processes. Following the coding, inter-rater reliability between the two researchers was calculated using Cohen's Kappa for categorical data (Cohen, 1988; Stock, 1994). A criterion of $\kappa = .70$ was employed (Fleiss, 1981; Gardner, 1995; Landis & Koch, 1977). The obtained inter-rater reliability ($\kappa = .89$) exceeded that criterion.

All subsequent analyses concerning coded data were conducted twice: once with the principal researcher's codes and once with the associate researcher's codes. Both sets of analyses produced the same answers to the research questions. To conserve space and avoid redundancy, only the analyses based on the principal researcher's codes are reported.

Dependent variables. The total sum of verbalizations was calculated for each micro self-regulated learning process. Miscellaneous verbalizations were not included in these calculations or the following analyses because they were not related to this research question.

Outlier analysis. An outlier analysis was completed for the sums of micro self-regulated learning processes. The modified z-score method uncovered 10 outliers across all six micro processes (i.e., within self motivation beliefs, monitoring, control, self-judgment, & self-reaction). As before, these outliers were replaced by the largest data point that was not an outlier in their respective data sets.

Analytic approach. Six one-sample *t*-tests evaluated whether each sum was significantly different than zero. Given that multiple *t*-tests were conducted, it was necessary to control for inflation of the Type I error rate. To do so, these six *t*-tests were deemed a family, and the Bonferroni adjustment was employed to maintain a family-wise error rate of .05. Accordingly, each *t*-test was evaluated at the $.05/6 = .008$ level.

Outcome. All self-regulated learning micro processes were found to be active (see Table 5). One-sample *t*-tests indicated that the sums for task analysis, $t(64) = 14.35, p < .001, d = 1.78$, self-motivation belief, $t(64) = 9.92, p < .001, d =$

1.23, monitoring, $t(64) = 11.39$, $p < .001$, $d = 1.67$, control, $t(64) = 14.21$, $p < .001$, $d = 1.76$, self-judgment, $t(64) = 8.55$, $p < .001$, $d = 1.06$, and self-reaction, $t(64) = 5.77$, $p < .001$, $d = 0.72$, were all significantly greater than zero.

Table 5

Sums, means, and standard errors of micro self-regulated learning processes.

Micro Process	Sum	$M (SE)$
Task Analysis	9,056	139.32 (9.71)
Self-Motivation Beliefs	696	10.71 (.79)
Monitor	9,963	153.28 (11.39)
Control	4,805	73.92 (5.02)
Self-Judgment	192	2.95 (.35)
Self-Reaction	74	1.14 (.20)

These results suggested that participants verbalized all of the self-regulated learning processes that are described by Zimmerman's (2000, 2002,

2011) and Pintrich's (2000, 2004) models of self-regulated learning. Thus, the results sufficed the second requirement of self-regulated learning.

Requirement #3: learning related to self-regulated learning processes.

The third requirement of self-regulated learning was that there must be evidence that learning was related to changes in the self-regulated learning processes exhibited by the participants. Following are analyses that investigated this.

Outlier analysis. An outlier analysis was completed for the sums of micro self-regulated learning processes in the beginning and in the end of the study. The modified z-score method uncovered 13 outliers across all six micro processes in the beginning (i.e., within task analysis, self motivation beliefs, monitoring, & self-judgment) and 8 outliers in the end (i.e., within task analysis, self-motivation beliefs, control, & self-judgment). As before, these outliers were replaced by the largest data point that was not an outlier in their respective data sets.

Please note that the outlier analysis was conducted on the sums of the micro self-regulated learning processes rather than the raw data that fed into those variables (i.e., sums per level). When the raw data were subjected to outlier analyses, a large number of outliers were identified. If each outlier had been modified, then the overall nature of the performance data could have substantially changed, which was undesirable. As such, it was decided to conduct

the outlier analysis on the sum of the self-regulated learning processes in the beginning and the end of the study as opposed to the raw data that fed into those calculations.

Dependent variables. To test Requirement #3, it was necessary to investigate the relationship between changes in performance across the study (i.e., learning) and changes in the frequency of self-regulated learning processes across the study. The dependent variables that were used to test Requirement #1 and Requirement #2 did not capture the constituent parts of that relationship. Therefore, two additional types of variables were created: variables representing learning and variables representing change in self-regulated learning processes. The creation of each type of variable is described below.

First, two learning variables were created by calculating the change in performance between the beginning of the study (i.e., Levels 3-6) and the end of the study (i.e., Levels 8-11) for average error_{portals} and average error_{time}. Those new variables are hereafter referred to as learning_{portals} and learning_{time}, respectively. These learning variables represent the extent to which each individual participant learned, as opposed to the average extent of learning for the entire group of participants as was the case with Requirement #1. A positive learning metric indicated that a participant had a greater average error_{portals} or

average error_{time} in the beginning than in the end of the study. A negative learning metric indicated that a participant had a greater average error_{portals} or average error_{time} in the end than in the beginning of the study. A zero learning metric indicated that a participant had no change in average error_{portals} or average error_{time} from the beginning to the end of the study.

Second, six self-regulated learning variables were created by calculating the change in the average sum of each micro self-regulated learning variable at the beginning of the study (i.e., Levels 3-6) from its counterpart at the end of the study (i.e., Levels 8-11). These six variables indicated the change in average sum of self-regulated learning variables from the beginning to the end of the study. A positive change metric indicated that the average sum of verbalizations decreased from the beginning of the study to the end of the study. A negative change metric indicated that the average sum of verbalizations increased from the beginning of the study to the end of the study. A zero change metric indicated that the average sum of verbalizations did not change from the beginning to the end of the study.

Analytic approach. Three sets of analyses were conducted. The following describes the purpose and exact nature of each set of analyses.

The first set of analyses explored whether the total sum of verbalizations significantly correlated with their performance. If correlated, this relationship may cause ambiguity in subsequent analyses. That is, it may be unclear whether learning would be related to a change in self-regulated learning processes or a change in the total number of verbalizations. To do so, the total sum of verbalizations was correlated with $\text{learning}_{\text{portals}}$ and $\text{learning}_{\text{time}}$. If the total sum of verbalizations was correlated with the learning variables, then subsequent analyses must account for the sum of verbalizations. Given that multiple correlations were significance tested, it was necessary to control for inflation of the Type I error rate. To do so, the correlations concerning $\text{learning}_{\text{portals}}$ and $\text{learning}_{\text{time}}$ were deemed a family, and the Bonferroni adjustment was employed to maintain a family-wise error rate of .05. Accordingly, each correlation was evaluated at the $.05/2 = .025$ level.

The second set of analyses explored whether participants' spatial abilities significantly correlated with their performance. To do so, participants' MRT scores were correlated with $\text{learning}_{\text{portals}}$ and $\text{learning}_{\text{time}}$ at the beginning and end of the study. If MRT scores significantly correlated with these learning variables, then subsequent analyses must account for MRT. Given that multiple correlations were significance tested, it was necessary to control for inflation of

the Type I error rate. To do so, the correlations concerning learning_{portals} and learning_{time} were deemed a family, and the Bonferroni adjustment was employed to maintain a family-wise error rate of .05. Accordingly, each correlation was evaluated at the $.05/2 = .025$ level.

The third set of analyses explored whether learning was related to self-regulated processes. To do so, analyses were conducted to understand what changes in the sums of micro self-regulated learning processes predicted learning_{portals} and learning_{time}. If either the sum of verbalizations or MRT were significantly correlated with learning, then the significant covariate would be entered into the first step of two hierarchical multiple regressions and the self-regulated learning variables would be entered into the second step. If both the sum of verbalizations and MRT were significantly correlated with learning, then the sum of verbalizations would be entered into the first step, MRT would be entered into the second step, and the self-regulated learning variables would be entered into the third step of two hierarchical multiple regressions. If neither sum of verbalizations nor MRT were significant related to learning, then only self-regulated learning variables would be entered into a simultaneous multiple regression.

Given that multiple variables were significance tested within each multiple regression, it was necessary to control for inflation of the Type I error rate. To do so, the correlations concerning learning_{portals} and learning_{time} were deemed a family, and the Bonferroni adjustment was employed to maintain a family-wise error rate of .05. Accordingly, each family was evaluated at the $.05/6 = .008$ level if only self-regulated learning variables were used as predictors, the $.05/7 = .007$ level if one covariate was also used as an additional predictor, or the $.05/8 = .006$ level if both covariates were used as additional predictors.

Outcome. The first set of analyses indicated that the participants' total number of verbalizations was positively correlated with learning_{portals} ($r = 0.46, p < .001$) and with learning_{time} ($r = 0.49, p < .001$). This suggested that the total sum of verbalizations may have influenced learning. Accordingly, the total sum of verbalizations was entered in the first step of the hierarchical multiple regression.

The second set of analyses indicated that MRT was neither significantly correlated with learning_{portals} ($r = -0.15, p = .23$) nor with learning_{time} ($r = -0.24, p = .06$). This suggested that participants' spatial abilities did not influence their learning. Accordingly, MRT was not entered in the second step of the hierarchical multiple regression. Rather, the the self-regulated learning variables entered into the second step.

When the total sum of verbalizations was entered into step 1, it accounted for 21.3% of the variance in learning_{portals}, $F(1, 64) = 17.10, p < .001$. Then, when the change in sums of task analysis, self motivation beliefs, monitoring, control, self-judgment, and self-reaction processes were entered in step 2, these variables accounted for an additional 29.0% of the variance in learning_{portals}, $F(7, 64) = 8.25, p < .001$. As shown in Table 6, the change in sum of monitoring ($\beta = .58, p < .001$) significantly predicted learning_{portals}. The remaining micro self-regulated learning processes did not significantly predict learning_{portals}. Multicollinearity among self-regulated learning processes was not considered to be problematic because no variance inflation factor (VIF) was greater than 10 (Hair, Anderson, Tatham, & Black, 1995). Therefore, accounting for the total number of verbalizations in step 1 likely removed the variance associated with how much participants spoke during the study.

Table 6

Change in the sum of self-regulated learning processes predicting learning_{portals}.

Predictor Variables	B	<i>B</i>	<i>t</i> -statistic	<i>VIF</i>
Step 1				
Verbalizations	2.18	0.46	4.14**	1.00
Step 2				
Verbalizations	2.54	0.54	4.75**	1.48
Task Analysis	1.55	0.06	0.48	2.02
Self Motivation	-3.74	-0.02	-0.14	1.56
Beliefs				
Monitoring	14.42	0.58	4.34**	2.05
Control	-6.94	-0.13	-1.01	1.74
Self-Judgment	-32.38	-0.07	-0.59	1.61
Self-Reaction	-112.00	-0.13	-1.25	1.28

Note: ** $p < .001$

When the total sum of verbalizations was entered into step 1, it accounted for 24.0% of the variance in learning_{time}, $F(1, 64) = 19.92$, $p < .001$. Then, when the change in sums of task analysis, self motivation beliefs, monitoring, control,

self-judgment, and self-reaction processes were entered in step 2, these variables accounted for an additional 61.1%% of the variance in learning_{time}, $F(7, 64) = 46.73, p < .001$. As shown in Table 7, the change in sum of task analysis ($\beta = .21, p = .006$) and monitoring ($\beta = .52, p < .001$) significantly predicted learning_{time}. The remaining micro self-regulated learning processes did not significantly predict learning_{time}. Multicollinearity among self-regulated learning processes was not considered to be problematic because no VIF metric was greater than 10. Therefore, accounting for the total number of verbalizations in step 1 likely removed the variance associated with how much participants spoke during the study.

Table 7

Change in the sum of self-regulated learning processes predicting learning_{time}.

Predictor Variables	B	β	t-statistic	VIF
Step 1				
Verbalizations	0.50	0.49	4.46*	1.00
Step 2				
Verbalizations	0.71	0.70	11.20**	1.48
Task Analysis	1.08	0.21	2.85*	2.02
Self Motivation Beliefs	6.05	0.12	1.91	1.56
Monitoring	2.78	0.52	7.07**	2.05
Control	1.70	0.14	2.09*	1.74
Self-Judgment	1.37	0.01	0.21	1.61
Self-Reaction	0.27	0.00	0.03	1.28

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

These results indicated that the third requirement for self-regulated learning was met. That is, there was a relationship between learning and changes in sums of self-regulated learning processes. Specifically, a decrease in the sum

of monitoring processes was significantly related to learning_{portals} and decreases in the sums of task analysis and monitoring processes were significantly related to learning_{time}.

Self-regulated learning implications. Three requirements were examined to determine whether participants self-regulated their learning as described by Zimmerman (2000, 2002, 2011) or Pintrich (2000, 2004). First, participants had to learn. Second, participants had to exhibit all of the self-regulated learning processes. Third, participants' learning had to be related to changes in their self-regulated learning processes. The results suggested that all three requirements were satisfied. Therefore, there was evidence that participants self-regulated their learning within this virtual simulation.

What is the Structure of Self-Regulated Learning?

Given that participants self-regulated their learning, analyses were conducted to determine which model of self-regulated learning (i.e., Zimmerman's or Pintrich's) best described the structure of the learners' self-regulated learning processes. To conclude that Zimmerman's model of self-regulated learning best fit that structure, there had to be evidence that the flow between self-regulated learning phases was cyclical (Zimmerman, 2000, 2002,

2011). Otherwise, it would be concluded that Pintrich's (2000, 2004) model best fit the structure of learners' self-regulated learning processes.

Dependent variables. To determine whether the flow of self-regulated learning processes resembled the structure described by Zimmerman (2000, 2002, 2011), it was pertinent to know the frequency that one macro self-regulated learning process transitioned to another macro process). Only macro self-regulated processes were included because Zimmerman's model does not specify the order in which micro self-regulated learning processes occur within macro self-regulated learning processes (Zimmerman, 2000).

Two types of transitional frequencies were calculated: lag 1 and lag 2 statistics (see Figure 5). Lag 1 statistics described the frequency that pairs of self-regulated learning processes were expressed one immediately after the other. For the purpose of this analysis, lag 1 statistics were limited to heterogeneous transitions, i.e., transitions from one macro self-regulated learning process to a different process. Allowing homogeneous transitions, i.e., transitions from one macro self-regulated learning process to the same process, would over-inflate the frequencies that processes transitioned to themselves, thus unnecessarily increasing the criterion for a transitional frequency to be considered significant. Moreover, homogeneous transitions were not related to Zimmerman's model

(2000, 2002, 2011). Lag 2 frequencies described the likelihood that pairs of self-regulated learning processes were expressed in close proximity, but with one verbalization in between. Transitional frequencies from one process to itself were permitted for lag 2 transitions because these transitions represent a process transitioning to itself after first transitioning to a different process. Therefore, they do not represent homogenous transitions. For both lag 1 and lag 2 transitional frequencies, a greater number indicated a greater instance of one process transitioning to another process. It was important to calculate both types of transitional frequencies because Zimmerman's model (2000, 2002, 2011) affords predictions in terms of both lag 1 and lag 2 statistics.

Figure 5. Depiction of lag 1 and lag 2 transitions

Analytic approach. A sequential analysis (Bakeman & Gottman, 1997) examined the relations between macro self-regulated learning processes. Each transition was tested for significance. Using a one-tailed test, if a given transition

had a z-score of 1.65 or greater ($\alpha = .05$), then it was considered significant. A significant transition indicated that the transitional frequency was significantly greater than its expected frequency, which was based on the null hypothesis that the processes associated with the transition were independent. Therefore, a significant transition indicated that the two corresponding macro processes were dependent, which suggested a sequential structure. In contrast, a non-significant transition indicated that the two corresponding macro processes were independent, which suggested a lack of sequential structure. Given that multiple z-scores were significance tested, it was necessary to control for inflation of the Type I error rate. To do so, the z-scores associated with the full set of transitions were deemed a family, and the Bonferroni adjustment was employed to maintain a family-wise error rate of .05. Accordingly, each z-score was evaluated at the $.05/9 = .006$ level.

The following conditions would have to be met in order to conclude that the observed transitions mirrored the cyclical structure of Zimmerman's (2000, 2002, 2011) model of self-regulated learning. First, there would have to be significant lag 1 transitions from forethought to performance, from performance to self-reflection, and from self-reflection to forethought (see Figure 6). In addition, there would have to be non-significant lag 1 transitions from

performance to forethought, from forethought to self-reflection, and from self-reflection to performance. Second, there would have to be significant lag 2 transitions from forethought to self-reflection, performance to forethought, and self-reflection to performance (see Figure 6). In addition, there would have to be non-significant lag 2 transitions from forethought to performance, performance to self-reflection, and from self-reflection to forethought. If any of these conditions were not met, then the observed flow of self-regulated learning processes would not mirror Zimmerman's structured model. Instead, the processes would be presumed to have no cyclical structure as proposed by Pintrich (2000, 2004).

Figure 6. Depiction of lag 1 and lag 2 transitions in relation to Zimmerman's (2000, 2002, 2011) model of self-regulated learning

Outcome. The transitional probabilities between macro self-regulated learning processes and their corresponding z-scores, calculated from the transitional and expected frequencies, are presented in the transitional diagrams

in Figures 7 and 8. Transitional probabilities are used in Figures 7 and 8 because they aid in the interpretation of the frequencies. Figure 7 contains the transitional probabilities and z-scores for the lag 1 sequential analyses (i.e., analysis of processes that directly follow another process). Figure 8 contains the transitional probabilities and z-scores for the lag 2 sequential analyses (i.e., analysis of processes that follow the processes after the lag 1 process). In the transitional diagrams, thick and thin lines indicate significant and non-significant transitions, respectively.

Figure 7. Lag 1 transitional probabilities (top) and z-scores (bottom) of the macro self-regulated learning processes. *Note:* ** $p < .001$

Figure 8. Lag 2 transitional probabilities (top) and z-scores (bottom) of the macro self-regulated learning processes. Note: ** $p < .001$

The following results of the significance tests supported the cyclical nature of Zimmerman's (2000, 2002, 2011) model. First, there were significant lag 1 transitions between forethought and performance (i.e., .99 probability) and from performance to self-reflection (i.e., .03 probability). Second, there was a significant lag 2 transition from forethought to self-reflection (i.e., .03 probability).

However, other results of the significance tests did not support the cyclical nature of Zimmerman's (2000, 2002, 2011) model. First, there were significant lag 1 transitions from self-reflection to performance (.63 probability) and from performance to forethought (.97 probability). Second, there were significant lag

2 transitions from self-reflection to forethought (.59 probability), from forethought to forethought (.96 probability), from performance to performance (.98 probability), and from self-reflection to self-reflection (.06 probability).

Taken together, the results suggested that participants exhibited the macro self-regulated learning processes in the cyclical order suggested by Zimmerman's (2000, 2002, 2011) model at least some of the time. However, participants also exhibited the macro processes in an order that was not consistent with Zimmerman's (2000, 2002, 2011) model. For example, the sequential analysis revealed that participants often switched back and forth from forethought to performance processes without exhibiting any self-reflection processes. Consequently, the evidence indicated that, contrary to Zimmerman's (2000, 2002, 2011) model, self-regulated learning processes did not form a completely cyclical pattern. Therefore, the processes are presumed to have a different or less organized structure as proposed by Pintrich (2000, 2004).

What were the Effects of Attrition?

Eight participants were omitted from the study because they ran out of time or elected to quit. It was important to understand whether the study's conclusions would have been different if the omitted participants had completed the study.

Analytic approach. Two approaches were employed to determine the impact of omitting certain participants from the study. First, demographic descriptive statistics for the participants who did and did not complete the study were compared. Second, performance data from a subset of the participants who did not complete the study were matched with performance data from participants who completed the study. That matched data was then added to the original data set. Following, the combined data set was subjected to analyses to estimate how the participants who did not complete the study would have impacted the results of the present study. The following provides details about each of these approaches. It is important to note that the second approach violates the assumption that each observation of the dependent variable was independent from other observations. However, the second approach was carried out because it was the most parsimonious approach to simulate the effects of attrition.

Comparing demographics. Independent samples t-tests compared age, MRT score, first-person perspective video game experience, military command / strategy video game experience, and puzzle game experience between participants who did and did not complete the study. These specific gaming experiences were selected because of their direct relevance to Portal. Given that

multiple t-tests were conducted, it was necessary to control for inflation of the Type I error rate. Because age, MRT, and video game experience are inherently different types of demographics, tests associated with each type of demographic were deemed a family. Because age and MRT required only one t-test per family, no Bonferroni adjustment was made. However, for video game experience, the Bonferroni adjustment was employed to maintain a family-wise error rate of .05. Accordingly, each *t*-test related to video game experience was evaluated at the $.05/3 = .02$ level.

Estimating participant performance. To determine the impact of attrition, it was necessary to estimate how the participants who did not complete the study would have performed had they completed the study. To do so, performance data from participants who did and did not complete the study were matched (see Table 8). Specifically, the average error_{portals} and average error_{time} from the beginning of the study (i.e., Levels 3-6) were calculated for the five participants who completed, at least, Level 6 but did not complete the study. Then, these error variables were matched with comparable average error_{portals} and average error_{time} values from participants who completed the study. Please note that the three other participants who did not complete the study were not included in this matching procedure because they provided very little data, which

made it impossible to calculate meaningful performance variables. Given this matching procedure, the two groups of five matched participants (i.e., those matched by average error_{portals} & those matched by average error_{time}) were combined into one group of 10 matched participants. These 10 matched participants were then added to the original 65 participants to create an overall sample of 75 participants.

Table 8

Participants who did not complete the study were matched with comparable participants who completed the study.

	Error in the beginning of the study (participants who did not complete the study)	Error in the beginning of the study (matched participants)	Error in the end of the study (matched participants)
Error_{portals}			
	25452.50	3717.50	919.58
	8227.50	3717.50	1178.75
	3750.00	3712.50	1151.67
	3132.50	3717.50	565.00
	625.00	632.50	392.50
Error_{time}			
	1178.51	913.89	376.21
	1080.79	913.89	265.60
	932.03	904.18	494.61
	710.37	723.93	494.61
	701.23	718.83	477.70

Once the matching procedure was complete, the expanded data (original and matched participants) were subjected to the same analyses that were applied

to the original data. That allowed us to determine whether the conclusions were impacted by attrition.

Outcome. Following is a discussion of whether the study's conclusions would have been different if the participants who were omitted had completed the study. First, results regarding the demographics are presented. Second, results regarding participant performance are presented.

Comparing demographics. Table 9 contains the demographic information of the 65 participants who completed the study, as well as the 8 participants who did not complete the study. As indicated in Table 8, there was no significant difference between those who did and did not complete the study in terms of age or video game experience. However, there was a significant difference between those groups in terms of MRT, $t(71) = 2.33, p < .05$. That is, participants who were omitted for not completing the study ($M = 6.25, SD = 3.28$) had a significantly lower MRT score than those who completed the study ($M = 10.52, SD = 5.04$).

Table 9

Comparison of demographics between participants who completed the study and participants who did not complete the study.

	Completed the study (N=65)		Did not complete the study (N=8)		<i>t</i>	<i>df</i>	<i>P</i>
	M	SD	M	SD			
Age	20.58	2.27	20.875	2.79987	-0.34	70	0.735
MRT	10.52	5.04	6.25	3.28416	2.328	71	0.023
First-person perspective	3.15	1.23	2.375	0.74402	1.749	71	0.085
Military command / strategy	2.89	1.19	1.875	0.64087	2.371	71	0.02
Puzzles	2.69	1.24	2.375	1.18773	0.688	71	0.494

Note: Age was represented by only 64 participants. One participant did not respond.

These results suggested the following. First, participants who did and did not complete the study appeared to be comparable in terms of age and video gaming experience. It should be noted, however, that there may have been insufficient power due to the size of the sample of participants who did not complete the study. Second, participants who did not complete the study differed from participants who completed the study in regard to MRT score. Therefore, including these participants may have impacted the relationship between MRT and performance in Requirement #1 of the first research question.

Estimating participant performance. To assess the potential impact of attrition on Requirement #1 of the first research question, two repeated measures ANCOVAs compared the performance of the combined sample at the beginning and end of the study to determine whether learning occurred. Regarding average error_{portals}, a test of the homogeneity-of-regression (slopes) assumption indicated that the relationship between MRT and average error_{portals} did not differ significantly as a function of when the data was collected (i.e., beginning of the study vs. end of the study) $F(1,73) = 1.64, p = .20$. Furthermore, the ANCOVA was significant, $F(1,73) = 18.29, p < .001$. That is, average error_{portals} in the beginning of the study ($M = 1336.53\%$, $SE = 145.17\%$) was significantly greater than the average error_{portals} from the end of the study ($M = 494.41\%$, $SE = 39.02\%$) while

accounting for MRT as a covariate. Regarding average error_{time}, a test of the homogeneity-of-regression (slopes) assumption indicated that the relationship between MRT and average error_{time} also did not differ significantly as a function of when the data was collected (i.e., beginning of the study vs. end of the study), $F(1,73) = 5.84, p = .02$. In addition, the ANCOVA was also significant, $F(1,73) = 24.50, p < .001$. That is, average error_{time} from the beginning of the study ($M = 357.30\%$, $SE = 31.17\%$) was significantly greater than average error_{time} at the end of the study ($M = 205.81\%$, $SE = 15.53\%$) while accounting for MRT as a covariate. These results indicated that the expanded sample of participants learned to play more efficiently and quickly over the course of the study, which is consistent with the original analyses. Therefore, it is unlikely that attrition impacted the results related to Requirement #1 of the first research question.

To assess the potential impact of attrition on Requirement #2 of the first research question, one-sample t -tests determined whether sums of self-regulated learning processes were significantly greater than zero to determine whether the combined sample verbalized all of the self-regulated learning processes. The results indicated that the sums for task analysis, $t(74) = 16.60, p < .001, d = 1.92$, self-motivation beliefs, $t(74) = 11.32, p < .001, d = 1.31$, monitoring, $t(74) = 13.24, p < .001, d = 1.53$, control, $t(74) = 14.02, p < .001, d = 1.62$, self-judgment,

$t(74) = 9.17, p < .001, d = 1.06$, and self-reaction, $t(74) = 5.99, p < .001, d = 0.69$ were all significantly greater than zero. Overall, these results demonstrated that participants exhibited all of the micro self-regulated learning processes, which is consistent with the original analyses. Thus, it is unlikely that attrition impacted the results related to Requirement #2 of the first research question.

Table 10

Sums, means, and standard errors of micro self-regulated learning processes of the combined sample.

Micro Process	Sum	Mean (SE)
Task Analysis	11,045	147.27 (8.87)
Self-Motivation Beliefs	908	12.11 (1.07)
Monitor	12,953	172.71 (13.04)
Control	6,336	84.48 (6.03)
Self-Judgment	248	3.12 (.36)
Self-Reaction	87	1.16 (.19)

To assess the potential impact of attrition on Requirement #3 of the first research question, two hierarchical multiple regressions were conducted. These regressions determined whether changes in micro self-regulated learning predicted learning. The total sum of verbalizations was entered in the first step of the hierarchical multiple regression because it was significantly related to learning_{portals} ($r = .52, p < .001$) and learning_{time} ($r = .55, p < .001$). MRT was not entered in any step because it was not significantly related to learning_{portals} ($r = -.15, p = .20$) and learning_{time} ($r = -.27, p = .02$).

Regarding learning_{portals}, when the total sum of verbalizations was entered into step 1, it accounted for 26.5% of the variance, $F(1, 74) = 26.37, p < .001$. Then, when the changes in sums of task analysis, self motivation beliefs, monitoring, control, self-judgment, and self-reaction processes were entered in step 2, these variables accounted for an additional 24.6% of the variance in learning_{portals}, $F(7, 74) = 10.02, p < .001$. As shown in Table 11, the change in sum of monitoring ($\beta = .57, p < .001$) significantly predicted learning_{portals}. The remaining micro self-regulated learning processes did not significantly predict learning_{portals}. Multicollinearity among self-regulated learning processes was not considered to be problematic because no VIF metric was greater than 10. Therefore, accounting for the total number of verbalizations in step 1 likely

removed the variance associated with how much participants spoke during the study.

Table 11

Changes in the sums of self-regulated learning processes predicting learning_{portals} for the combined sample.

Predictor Variables	B	<i>B</i>	<i>t</i> -statistic	<i>VIF</i>
Step 1				
Verbalizations	2.56	.52	5.14**	1.00
Step 2				
Verbalizations	2.53	.51	4.75**	1.58
Task Analysis	.72	.03	.23	1.98
Self Motivation	-14.76	-.06	-.52	1.69
Beliefs				
Monitoring	15.02	.57	4.74**	1.98
Control	-9.56	-.16	-1.35	1.99
Self-Judgment	-50.69	-.11	-.91	1.89
Self-Reaction	-142.31	-.14	-1.46	1.29

Note: * $p < .001$

Regarding learning_{time}, when the total sum of verbalizations was entered into step 1, it accounted for 29.8% of the variance, $F(1, 74) = 30.95, p < .001$. Then, when the change in sums of task analysis, self motivation beliefs, monitoring, control, self-judgment, and self-reaction processes were entered in step 2, these variables accounted for an additional 58.7% of the variance in learning_{time}, $F(7, 74) = 30.95, p < .001$. As shown in Table 12, the change in sum of task analysis ($\beta = .19, p = .001$) and monitoring ($\beta = .52, p < .001$) significantly predicted learning_{time}. The remaining micro self-regulated learning processes did not significantly predict learning_{time}. Multicollinearity among self-regulated learning processes was not considered to be problematic because no VIF metric was greater than 10. Therefore, accounting for the total number of verbalizations in step 1 likely removed the variance associated with how much participants spoke during the study.

Table 12

Changes in the sums of self-regulated learning processes predicting learning_{portals} for the combined sample.

Predictor Variables	B	<i>B</i>	<i>t</i> -statistic	<i>VIF</i>
Step 1				
Verbalizations	0.57	0.55	5.56**	1.00
Step 2				
Verbalizations	0.69	0.67	12.76	1.48
Task Analysis	1.05	0.19	3.32*	2.02
Self Motivation Beliefs	6.23	0.12	2.17	1.56
Monitoring	2.87	0.52	8.93**	2.05
Control	1.52	0.12	2.11	1.74
Self-Judgment	-1.46	-0.02	-0.26	1.61
Self-Reaction	2.31	0.01	0.23	1.28

*Note: *p < .001*

The results indicated that learning was related to changes in the monitoring and task analysis self-regulated learning processes, which is consistent with the original analyses. Accordingly, it is unlikely that attrition impacted the results related to Requirement #3 of the first research question.

To assess the potential impact of attrition on the second research question, a sequential analysis was performed. The lag 1 and lag 2 transitional probabilities between macro self-regulated learning processes and their corresponding z-scores are presented in the transitional diagrams in Figures 9 and 10, respectively. In the transitional diagrams, thick and thin lines indicate significant and non-significant transitions, respectively.

Figure 9. Lag 1 transitional probabilities (top) and z-scores (bottom) of the combined sample's (N = 75) macro self-regulated learning processes.. Note: One-tailed, ** $p < .001$

Figure 10. Lag 2 transitional probabilities (top) and z-scores (bottom) of the combined sample's (N = 75) macro self-regulated learning processes. Note: One-tailed, ** $p < .001$

The following results of the significance tests supported the cyclical nature of Zimmerman's (2000, 2002, 2011) model. First, there were significant lag 1 transitions between forethought and performance (i.e., .99 probability) and from performance to self-reflection (i.e., .03 probability). Second, there was a significant lag 2 transition from forethought to self-reflection (i.e., .03 probability). These results of the combined sample were consistent with the results of the present study.

Other results of the significance tests did not support the cyclical nature of Zimmerman's (2000, 2002, 2011) model. First, there were significant lag 1 transitions from self-reflection to performance (.66 probability) and from

performance to forethought (.97 probability). Second, there were significant lag 2 transitions from self-reflection to forethought (.62 probability), from forethought to forethought (.96 probability), from performance to performance (.98 probability), and from self-reflection to self-reflection (.06 probability). These results of the combined sample were consistent with the results of the present study.

Taken together, the results indicated that participants did not exhibit self-regulated learning processes in the cyclical manner described by Zimmerman (2000, 2002, 2011), which is consistent with the original analyses. Therefore, it is unlikely that attrition impacted the results related to the second research question.

Implications. Overall, it does not appear that attrition impacted the results of the present study for two reasons. First, despite the fact that participants who did and did not complete the study differed in terms of MRT, use of MRT as a covariate produced the same outcome in the analyses of the combined sample data and the original sample data. Second, the analysis of the combined sample produced the same outcomes to the two research questions as the analysis of the original sample in the present study.

CHAPTER IV. CONCLUSIONS

Virtual simulations have helped to make training more accessible, especially enabling trainees to learn on their own during free time. However, training on one's own relies on motivational and cognitive processes that differ from those employed when training with instructors. Specifically, training on one's own should be most successful when trainees exhibit self-regulated learning processes. As described by Zimmerman (2000, 2002, 2011) and Pintrich (2000, 2004), self-regulated learning processes include task analysis, self-motivational beliefs, monitoring, control, self-judgment, and self-reaction.

Three studies have shed some light on how trainees self-regulate their learning within virtual simulations. However, none of the studies included all of the processes described by Zimmerman (2000, 2002, 2011) or Pintrich (2000, 2004). Therefore, there is no clear understanding whether trainees are actually self-regulating their learning within virtual simulations. If not, virtual simulations may not be as effective for training on one's own as the media has anecdotally suggested (Fletcher, 2009).

Addressing Gaps in Previous Research

The current study addressed multiple gaps in previous research. First, no study had used a complete model of self-regulated learning to test whether learners self-regulated their learning within a virtual simulation. Thus, the primary purpose of this study was to assess whether learners who were using a virtual simulation self-regulated their learning in accordance with Zimmerman's (2000, 2002, 2011) and Pintrich's (2000, 2004) models. Second, because no complete model of self-regulated learning has been evaluated within a virtual simulation, it was unclear whether the processes have cyclical dependences on each other, as suggested by Zimmerman (2000, 2002, 2011), or lack a cyclical structure, as suggested by Pintrich (2000, 2004). Thus, the secondary purpose of the present study was to assess which model best described the structure of learners' self-regulated learning processes.

Our Findings

Participants self-regulated their learning. To conclude that trainees self-regulated their learning, there had to be evidence that a) learning took place, b) all three phases of the self-regulated learning models were active at least once during the task, and c) learning was related to changes in self-regulated learning

processes. In sum, all three requirements were met. Following is a breakdown of those findings.

First, there was evidence that participants learned. That is, they were able to reduce their average $\text{error}_{\text{portals}}$ and $\text{error}_{\text{time}}$ from the beginning to the end of the study. In other words, participants learned how to play Portal more efficiently (i.e., they reduced average $\text{error}_{\text{portals}}$) and quickly (i.e., they reduced average $\text{error}_{\text{time}}$) throughout the study. These results sufficed the first requirement of self-regulated learning.

Second, there was evidence that participants verbalized all of the micro self-regulated learning processes. Despite this, 96% of the processes were task analysis, monitoring, and control processes. These processes involved activities such as surveying the context, setting goals, selecting strategies, executing strategies, and determining whether the strategies were successful. These three processes seem to support the actions involved in completing a learning task. The remaining 4% of the processes were self-motivation beliefs, self-judgment, and self-reaction processes. These processes seem to support the assessment of whether the participant wanted to continue the learning activity, reflections regarding how well they performed, why they performed that way, and how they would incorporate what they learned into future performance.

There are two plausible reasons why participants exhibited few self-motivation beliefs, self-judgment, and self-reaction processes. First, participants may have engaged these three processes, but not verbalized them. In this case, participants may have not had access to them in their working memory (Jaaskelainen, 2011) or the think-aloud protocol may have slowed down how quickly participants were able to process events within the game (Ericsson & Simon, 1993). In this case, priority of verbalization may have been given to the processes that were most directly related to performance (i.e., task analysis, monitoring, & control) within Portal given the fast-paced nature of the game. Second, participants may have not frequently engaged in these processes. In this case, these self-regulated learning processes may not have been required by the task of playing Portal or the nature of the study dissuaded these types of processes. For example, self motivation beliefs may have not been addressed due to the known compensation at the end of the study. Either way, further investigation is warranted.

Third, there was evidence that learning was related to changes in the frequency of these processes from the beginning to the end of the study. Specifically, a decrease in the number of monitoring processes predicted

learning_{portals}. In addition, decreases in the numbers of task analysis, monitoring, and control processes predicted learning_{time}.

For both dependent variables, a decrease in the frequency of monitoring processes and task analysis predicted increased learning. Why might that be? It is possible that the number verbalizations indicating confusion (e.g., "I don't know" & "This is difficult") or the identification of alternative strategies (e.g., "I'm going to try to shoot a portal across the room") decreased as participants' performance improved. Alternatively, it is also possible that those who learned may have experienced some automation of processes between the beginning and the end of the study (Star, 2000). Specifically, participants may have begun the study being conscious of the step-by-step processes within their working memory. Thus, participants were able to verbalize those processes. By the end of the study, many of those processes (e.g., task analysis, monitoring, & control) may have become more implicit and less easy to express (Berry & Broadbent, 1984). Thus, this potential automation of processes may have contributed to a reduction in the amount of time it took for participants to complete the levels in the end of the study and how efficiently they did so. However, additional studies would be required to investigate this potential explanation.

Self-regulated learning processes were not cyclical. To conclude that Zimmerman's model best fit the structure of participants' self-regulated learning processes, there had to be evidence that the flow between self-regulated learning phases was cyclical (Zimmerman, 2000, 2002, 2011). Otherwise, it would be concluded that Pintrich's (2000, 2004) model best fit the structure of learners' self-regulated learning processes.

There was no evidence to suggest that the flow of the verbalizations mirrored the cyclical structure suggested by Zimmerman. Instead, it appeared that participants may have exhibited the self-regulated learning processes in a flexible, non-linear order that was adapted to the learning task at hand, as described by Pintrich. Given these results, it is likely that a cyclical structure of the self-regulated learning processes was not required for the task of playing Portal.

Practical Implications

These results have practical implications. Specifically, participants self-regulated their learning within the virtual simulation. This provides some preliminary support that virtual simulations can be supplied to trainees for the purpose of self-learning.

Even though the results of this study indicated that participants self-regulated their learning, three of the six micro self-regulated learning processes were infrequently verbalized. It is possible that interacting with virtual simulations may not require all of the micro self-regulated learning processes to be frequently exhibited. Instead, the nature of this task may be highly reliant on task analysis, monitoring, and control. Nonetheless, this introduces a risk that some learners may not exhibit all of the self-regulated learning processes within a virtual simulation, especially self-judgment and self-reaction, which occurred least frequently. Not exhibiting all of the processes may negatively impact learning effectiveness. Future studies should investigate this risk further.

In addition, the results indicated that participants exhibited self-regulated learning processes in a way that differed from Zimmerman (2000, 2002, 2011). If the exhibition of these processes is truly task dependent, then a “one size fits all” approach should not be adopted when designing training programs. That is, a trainer should be aware that how trainees self-regulate their learning may vary from task to task. Not understanding how self-regulated learning differs in multiple environments may render the training of self-regulated learning behavior ineffective. Future studies should investigate the flow in which trainees exhibit self-regulated learning processes within multiple types of virtual

simulations to better understand how task constraints affect the processes that are exhibited while self-regulating learning.

Once these two risks are better understood, there are opportunities to foster self-regulated learning behavior within training programs. For example, training programs can implement mechanisms to scaffold self-regulated learning processes. Specifically, these training programs could prompt the trainee to answer questions related to self-regulated learning processes (e.g., "What is your strategy?", "How well is your strategy working?", "How do you intend to approach similar tasks in the future?"). These questions may appear more frequently in the beginning of training and less frequently toward the end of training with the expectation that trainees would begin to self-regulate their own learning. In addition, these questions could be presented in an order that best fits the task being trained in the virtual simulation once that order is determined.

Future Research

The results of the current study identified opportunities for future research. These opportunities are as follows.

First, the results of this study determined that participants self-regulated their learning in this virtual simulation. However, we did not examine why participants verbalized some micro self-regulated learning processes more

frequently (i.e., task analysis, monitoring, & control) and other processes less frequently (i.e., self motivational beliefs, self-judgment, & self-reflection). It was unclear whether participants used these processes more frequently but did not verbalize them or simply did not use these processes frequently. Future research should examine these possibilities.

Second, the results of the study also determined that learning was related to a reduction in certain self-regulated learning processes. However, we did not examine why participants who increased their performance (i.e., learned) reduced the number of verbalizations of these processes. It is unclear whether these processes were no longer required or these processes became more automatic. Future research should also examine these two alternatives.

REFERENCES

- Abdi, H., & Williams, L. J. (2010). Contrast Analysis. In N. Salkind (Ed.), *Encyclopedia of Research Design*. Thousand Oaks, CA: Sage.
- Bandura, A. (1986). Social foundations of thought and action: a social cognitive theory: Prentice-Hall.
- Bandura, A. (1997). *Self-efficacy: the exercise of control*. New York: W.H. Freeman.
- Baxter, H. C., Harris-Thompson, D., & Phillips, J. K. (2004). *Sensemaking: A cognitive approach to training situation awareness skills*. Paper presented at the The Interservice/Industry Training, Simulation & Education Conference.
- Baxter, H. C., Ross, K., Phillips, J., Shafer, J., & Fowlkes, J. E. (2004). *Framework for the assessment of tactical decision-making simulations*. Paper presented at the Interservice/Industry Training, Simulation, and Education Conference, Orlando, FL.
- Bell, B., & Kozlowski, S. (2010). Toward a theory of learner-centered training design. In S. Kozlowski & E. Salas (Eds.), *Learning, Training, and Development in Organizations*. New York: Taylor & Francis.
- Berry, D. C., & Broadbent, D. E. (1984). On the relationship between task performance and associated verbalizable knowledge. *The Quarterly Journal*

of Experimental Psychology Section A, 36(2), 209-231. doi:

10.1080/14640748408402156

Berry, D. C., & Broadbent, D. E. (1987). The combination of explicit and implicit learning processes in task control. *Psychological Research*, 49(1), 7-15. doi: 10.1007/bf00309197

Boulos, M., Hetherington, L., & Wheeler, S. (2007). Second Life: an overview of the potential of 3-D virtual worlds in medical and health education. *Health Information and Libraries Journal*, 24(4), 233-245. doi: citeulike-article-id:1933634

Cannon-Bowers, J., & Bowers, C. (2010). Synthetic Learning Environments: On Developing a Science of Simulation, Games, and Virtual Worlds for Training. In S. Kozlowski & E. Salas (Eds.), *Learning, Training, and Development in Organizations*. New York: Taylor & Francis.

Carroll, J. S., & Payne, J. W. (1977). Judgments about crime and the criminal: A model and a method for investigating parole decisions. In B. D. Sales (Ed.), *Perspectives in law and psychology* (Vol. 1, pp. 191-239). New York: Plenum.

Cleary, T. J., & Zimmerman, B. J. (2001). Self-Regulation Differences during Athletic Practice by Experts, Non-Experts, and Novices. *Journal of Applied Sport Psychology*, 13(2), 185-206.

- Cleary, T. J., Zimmerman, B. J., & Keating, T. (2006). Training Physical Education Students to Self-Regulate During Basketball Free Throw Practice. *Research Quarterly for Exercise and Sport*, 77(2), 251-262.
- Cohen, M. S., Freeman, J. T., & Wolf, S. (1996). Metarecognition in Time-Stressed Decision Making: Recognizing, Critiquing, and Correcting. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 38(2), 206-219.
doi: 10.1518/001872096779048020
- DoD. (1998). Department of Defense Modeling and Simulation (M&S) Glossary: Department of Defense.
- Dominowski, R. L. (1998). Verbalizing and problem solving. In D. J. Hacker, J. Dunlosky & A. C. Graesser (Eds.), *Metacognition in educational theory and practice*. Mahwah, NJ: L. Erlbaum Associates.
- Dunlosky, J., & Lipko, A. R. (2007). Metacomprehension. *Current Directions in Psychological Science*, 16(4), 228-232. doi: 10.1111/j.1467-8721.2007.00509.x
- Dunlosky, J., & Metcalfe, J. (2009). *Metacognition*. Thousand Oaks, CA: Sage.
- Dunlosky, J., Serra, M. J., & Baker, J. M. C. (2008). Metamemory *Handbook of Applied Cognition* (pp. 137-161): John Wiley & Sons Ltd.

- Dweck, C. S. (1986). Motivational Processes Affecting Learning. *American Psychologist*, 41(10), 1040-1048. doi: 10.1037/0003-066x.41.10.1040
- Dweck, C. S., & Leggett, E. L. (1988). A Social-Cognitive Approach to Motivation and Personality. *Psychological Review*, 95(2), 256-273.
- Eccles, J. S. (1983). Expectancies, values, and academic behaviors. In J. T. Spence (Ed.), *Achievement and achievement motives: psychological and sociological approaches*. San Francisco: W.H. Freeman.
- Ericsson, K. A., & Simon, H. A. (1984). *Protocol analysis: verbal reports as data*. Cambridge, MA: MIT Press.
- Ericsson, K. A. & Simon, H. A. (1993). *Protocol analysis: Verbal reports as data*. Revised edition. Cambridge, MA: The MIT Press
- Ertmer, P. A., & Newby, T. J. (1996). The expert learner: Strategic, self-regulated, and reflective. *Instructional Science*, 24(1), 1-24. doi: 10.1007/bf00156001
- Fiore, S., & Cooke, N. J. (2010). Cognitive science based principles for the design and delivery of training. In S. Kozlowski & E. Salas (Eds.), *Learning, Training, and Development in Organizations* (pp. 169-201). New York: Taylor & Francis.

- Flavell, J. H. (1979). Metacognition and cognitive monitoring: A new area of cognitive-developmental inquiry. *American Psychologist*, 34(10), 906-911. doi: 10.1037/0003-066x.34.10.906
- Flavell, J. H. (1987). *Speculation about the nature and development of metacognition*. Hillsdale, NJ: L. Erlbaum Associates.
- Fletcher, J. D. (2009). Education and Training Technology in the Military. *Science*, 323(5910), 72-75. doi: 10.1126/science.1167778
- Ford, J. K., Smith, E. M., Weissbein, D. A., Gully, S. M., & Salas, E. (1998). Relationships of Goal Orientation, Metacognitive Activity, and Practice Strategies With Learning Outcomes and Transfer. *Journal of Applied Psychology*, 83(2), 218-233.
- Ford, J. K., Smith, E. M., Weissbein, D. A., Gully, S. M., & Salas, E. (1998). Relationships of Goal Orientation, Metacognitive Activity, and Practice Strategies With Learning Outcomes and Transfer. *Journal of Applied Psychology*, 83(2), 218-233.
- Garris, R., Ahlers, R., & Driskell, J. E. (2002). Games, Motivation, and Learning: A Research and Practice Model. *Simulation & Gaming*, 33(4), 441-467. doi: 10.1177/1046878102238607

- Greene, J. A., & Azevedo, R. (2010). The Measurement of Learners' Self-Regulated Cognitive and Metacognitive Processes While Using Computer-Based Learning Environments. *Educational Psychologist*, 45(4), 203-209. doi: 10.1080/00461520.2010.515935
- Greene, J. A., Bolick, C. M., & Robertson, J. (2010). Fostering historical knowledge and thinking skills using hypermedia learning environments: The role of self-regulated learning. *Computers & Education*, 54(1), 230-243. doi: 10.1016/j.compedu.2009.08.006
- Heiphetz, A., & Woodill, G. (2009). Training and Collaboration with Virtual Worlds: How to Create Cost-Saving, Efficient and Engaging Programs: McGraw-Hill.
- Huitema, B.E. (1980). The analysis of covariance. New York: Wiley.
- Iglewicz, B., & Hoaglin, D. (1993). *How to Detect and Handle Outliers* (Vol. 16). Milwaukee, WI.
- Jaaskelainen, R. (2011). Back to basics: Designing a study to determine the validity and reliability of verbal report data on translation processes. London: Continuum International Publishing Group.
- Johnson, E. J., & Russo, J. E. (1978). What is remembered after a purchase decision?

- Kennedy, H. (1999, November). Simulation reshaping military training. *National Defense*.
- Kirwan, B., & Ainsworth, L. K. (1992). *A Guide to task analysis*: Taylor & Francis.
- Kukreja, U., Stevenson, W., & Ritter, F. (2006). RUI: Recording user input from interfaces under Windows and Mac OS X. *Behavior Research Methods*, 38(4), 656-659. doi: 10.3758/bf03193898
- Loper, A. B., Hallahan, D. P., & Ianna, S. O. (1982). Meta-attention in learning disabled and normal students. *Learning Disability Quarterly*, 5(1), 29-36.
- Mann, J., Lyons, J., & de la Cruz, J. (2008). *Using Real-time Physics to Enhance Game Based Effects*. Paper presented at the The Interservice/Industry Training, Simulation & Education Conference, Orlando, FL.
- Mantovani, F. (2001). VR learning: Potential and challenges for the use of 3D environments in education and training. In G. R. C. Galimberti (Ed.), *Towards CyberPsychology*. Amsterdam: IOS Press.
- Matthews, P. (2010). More than meets the Eye: Approaches to maintenance training. *Military Training & Simulation News*, 12(6), 24-30.
- Nelson, T. O., & Narens, L. (2011). *Metamemory: a theoretical framework and new findings*. New York: Elsevier Science.

- Nietfeld, J., Hoffmann, K., McQuiggan, S., & Lester, J. (2008). *Self-Regulated Learning in a Narrative Centered Learning Environment*. Paper presented at the Proceedings of World Conference on Educational Multimedia, Hypermedia and Telecommunications 2008, Chesapeake, VA.
- Orvis, K. A., Horn, D. B., & Belanich, J. (2006). Videogame-Based Training Success: The Impact of Trainee Characteristics - Year 2. Alexandria, VA: Army Research Institute for the Behavioral and Social Sciences.
- Pajares, F., & Miller, M. D. (1994). Role of self-efficacy and self-concept beliefs in mathematical problem solving: A path analysis. *Journal of Educational Psychology*, 86(2), 193-203. doi: 10.1037/0022-0663.86.2.193
- Parajes, F. (2008). Motivational Role of Self-Efficacy Beliefs. In D. H. Schunk & B. J. Zimmerman (Eds.), *Motivation and self-regulated learning: theory, research, and applications*. New York: Lawrence Erlbaum Associates.
- Phillips, J., McDermott, P. L., Thordsen, M., McCloskey, M., & Klein, G. (1998). Cognitive requirements for small unit leaders in military operations in urban terrain: U.S. Army Research Institute for the Behavioral and Social Sciences.

- Pintrich, P. (2004). A Conceptual Framework for Assessing Motivation and Self-Regulated Learning in College Students. *Educational Psychology Review*, 16(4), 385-407. doi: 10.1007/s10648-004-0006-x
- Pintrich, P. R., Smith, D. A. F., Garcia, T., & McKeachie, W. J. (1991). *A manual for the use of the Motivated Strategies for Learning Questionnaire (MSLQ)*. Ann Arbor: National Center for Research to Improve Postsecondary Teaching and Learning.
- Pintrich, P. R., Wolters, C. A., & Baxter, G. P. (2000). Assessing Metacognition and Self-regulated Learning. In G. J. Schraw & J. C. Impara (Eds.), *Issues in the measurement of metacognition*. Lincoln, NE: Buros Institute of Mental Measurements and Department of Educational Psychology, University of Nebraska-Lincoln.
- Portal Walkthroughs. (2011), from <http://www.portalwalkthroughs.com/walkthrough/category/portal-guide/>
- Prensky, M. (2001). True believers: Digital game-based learning in the military *Digital Game-Based Learning*: McGraw-Hill.
- Pressley, M., & Woloshyn, V. (1995). Cognitive strategy instruction that really improves children's academic performance: Brookline Books.
- Rice, W. R. (1988). Analyzing Tables of Statistical Tests. *Evolution*, 43(1), 223-225.

Rosenthal, T. L., & Zimmerman, B. J. (1978). *Social learning and cognition*: Academic Press.

Ryan, R. M., & Deci, E. L. (2002). Overview of Self-Determination Theory: An Organismic Dialectical Perspective. In E. L. Deci & R. M. Ryan (Eds.), *Handbook of self-determination research*. Rochester, NY: University of Rochester Press.

Schoenfeld, A. H. (1987). *Cognitive science and mathematics education*. Hillsdale, NJ: Lawrence Erlbaum Associates.

Schraw, G., & Lehman, S. (2001). Situational Interest: A Review of the Literature and Directions for Future Research. *Educational Psychology Review*, 13(1), 23-52. doi: 10.1023/a:1009004801455

Schunk, D. H. (2001). Social cognitive theory and self-regulated learning. In B. J. Zimmerman & D. H. Schunk (Eds.), *Self-regulated learning and academic achievement: theoretical perspectives* (pp. 125-151). Mahwah, NJ: Lawrence Erlbaum Associates Publishers.

Schunk, D. H., Pintrich, P. R., & Meece, J. L. (2008). *Motivation in education: theory, research, and applications*: Pearson/Merrill Prentice Hall.

Schunk, D. H., & Usher, E. L. (2011). *Assessing self-efficacy for self-regulated learning*. New York, NY: Routledge.

- Schunk, D. H., & Zimmerman, B. J. (2008). *Motivation and self-regulated learning: theory, research, and applications*: Lawrence Erlbaum Associates.
- Smelik, R. M., Tutenel, T., Kraker, K. J. d., & Bidarra, R. (2010). Declarative terrain modeling for military training games. *Int. J. Comput. Games Technol.*, 2010, 1-11. doi: 10.1155/2010/360458
- Smith, R. D. (2007). *Five Forces of Game Technology Adoption in Military Simulation*. Paper presented at the SimTecT, Brisbane, Australia.
- Steam Users Forums. (2011), from <http://forums.steampowered.com/forums/showthread.php?t=609503>
- Tabachnick, B. G., & Fidell, L. S. (1989). *Using multivariate statistics* (2nd ed.). Cambridge: Harper & Row.
- Vandewalle, D. (1997). Development and Validation of a Work Domain Goal Orientation Instrument. *Educational and Psychological Measurement*, 57(6), 995-1015. doi: 10.1177/0013164497057006009
- Vogel, J., Vogel, D., Bowers, J., Bowers, C., Muse, K., & Wright, M. (2006). Computer Gaming and Interactive Simulations for Learning: A Meta-Analysis. *Journal of Educational Computing Research*, 34(3), 229-243. doi: citeulike-article-id:4783491

- Vu, K.-P. L., Hanley, G. L., Strybel, T. Z., & Proctor, R. W. (2000). Metacognitive Processes in Human-Computer Interaction: Self-Assessments of Knowledge as Predictors of Computer Expertise. *International Journal of Human-Computer Interaction*, 12(1), 43-71. doi: 10.1207/s15327590ijhc1201_2
- Wade, C., & Tavis, C. (2004). *Invitation to psychology* (Second ed.). Upper Saddle River, NJ: Pearson Hall.
- Walker, A. D., Carpenter, T. L., Moss, J. D., Switzer, F. S., Hoover, A. W., & Muth, E. R. (2009). The evaluation of virtual environment training for a building clearing task. *Human Factors and Ergonomics Society Annual Meeting Proceedings*, 53, 1206-1209. doi: 10.1518/107118109x12524443345997
- Wankel, C., & Kingsley, J. (2009). Higher education in virtual worlds: teaching and learning in Second Life: Emerald Group Pub.
- Weinstein, C. E., Schulte, A. C., & Palmer, D. R. (1987). *LASSI: learning and study strategies inventory. Booklet. User's manual*. Clearwater, FL: H & H Publishing.
- Wiener, E. L., & Nagel, D. C. (1989). *Human Factors in Aviation*: Academic Press.

- Wigfield, A. (1994). Expectancy-value theory of achievement motivation: A developmental perspective. *Educational Psychology Review*, 6(1), 49-78.
doi: 10.1007/bf02209024
- Wigfield, A., & Eccles, J. S. (1992). The development of achievement task values: A theoretical analysis. *Developmental Review*, 12(3), 265-310. doi: 10.1016/0273-2297(92)90011-p
- Winne, P. H. (2001). Self-regulated learning viewed from models of information processing. In B. J. Zimmerman & D. H. Schunk (Eds.), *Self-regulated learning and academic achievement: theoretical perspectives*. Mahwah, NJ: Lawrence Erlbaum Associates Publishers.
- Winne, P. H., & Hadwin, A. F. (1998). Studying as self-regulated learning. In D. J. Hacker, J. Dunlosky & A. C. Graesser (Eds.), *Metacognition in educational theory and practice*. Hillsdale, NJ: Lawrence Erlbaum.
- Winne, P. H., & Hadwin, A. F. (2008). The weave of motivation and self-regulated learning. In D. H. Schunk & B. J. Zimmerman (Eds.), *Motivation and self-regulated learning: theory, research, and applications*. Mahwah, NJ: Lawrence Erlbaum Associates.

- Winne, P. H., & Perry, N. E. (2000). Measuring self-regulated learning. In M. Boekaerts, M. Zeidner & P. R. Pintrich (Eds.), *Handbook of self-regulation*. San Diego, CA: Academic.
- Winters, F., Greene, J., & Costich, C. (2008). Self-Regulation of Learning within Computer-based Learning Environments: A Critical Analysis. [Article]. *Educational Psychology Review*, 20(4), 429-444. doi: 10.1007/s10648-008-9080-9
- Wolters, C. A. (2010). *Self-regulated Learning and the 21st Century Competencies*. <http://www.hewlett.org/library/grantee-publication/self-regulated-learning-and-21st-century-competencies>. The William and Flora Hewlett Foundation.
- Zap, N., & Code, C. (2009). Self-regulated learning in video game environments: Implications for educational gaming. In R. E. Ferdig (Ed.), *Handbook of research on effective electronic gaming in education*. New York, NY: Information Science Reference.
- Zimmerman, B. J. (2000). Attaining theories and models of self-regulation. In M. Boekaerts, M. Zeidner & P. R. Pintrich (Eds.), *Handbook of self-regulation*. San Diego, CA: Academic.

Zimmerman, B. J. (2005). Attaining self-regulation: A social cognitive perspective.

In M. Boekaerts, P. R. Pintrich & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 13-39). San Diego, CA: Academic Press.

Zimmerman, B. J., & Schunk, D. H. (2011). Motivational sources and outcomes of self-regulated learning and performance. New York, NY: Routledge.

APPENDIX A

RESULTS OF MATCHED PARTICIPANTS

The data from the matched participants ($N = 10$) was subjected to the same set of analyses that what was presented in the current study. Following this analysis, the data from the matched participants was combined with the data from the participants who completed the study to understand the effects of attrition.

Estimating participant performance. First, repeated measures ANCOVAs compared the performance of the matched participants at the beginning and end of the study to determine whether learning occurred. A test of the homogeneity-of-regression (slopes) assumption indicated that the relationship between MRT and average error_{portals} did not differ significantly as a function of when the data was collected (i.e., beginning of the study vs. end of the study), $F(1,8) = .617, p = .62$. Furthermore, the ANCOVA was not significant, $F(1,8) = 1.50, p = .26, d = 2.23$. That is, average error_{portals} in the beginning of the study ($M = 2898.25\%, SE = 402.30\%$) was not significantly different from the average error_{portals} from the end of the study ($M = 946.88\%, SE = 78.72\%$) while accounting for MRT as a covariate. Next, a test of the homogeneity-of-regression (slopes) assumption indicated that the relationship between MRT and average error_{time} also did not differ significantly as a function of when the data

was collected (i.e., beginning of the study vs. end of the study), $F(1,8) = 1.39$, $p = .27$. In addition, the ANCOVA was also non-significant, $F(1,8) = 5.79$, $p = .04$, $d = 1.48$. That is, average error_{time} from the beginning of the study ($M = 684.26\%$, $SE = 62.05\%$) was not significantly different than average error_{time} at the end of the study ($M = 380.14\%$, $SE = 32.33\%$) while accounting for MRT as a covariate.

These results suggested that the matched participants did not learn to play more efficiently or quickly over the course of the study. At face value, that suggested that the participants who did not complete the study would not have learned if they had completed the study, which contrasts with the conclusion drawn from the sample of participants who completed the study. A different story emerges, though, if one goes beyond face value. For example, matched participants' performance markedly improved over the course of the study. Specifically, matched participants' average error_{portals} improved nearly 2000% over the course of the study (average error_{portals} at the beginning of the study = 2898.25%, average error_{portals} at the end of the study = 946.88%). Similarly, matched participants' average error_{time} improved more than 300% over the course of the study (average error_{time} at the beginning of the study = 684.26%, average error_{time} at the end of the study = 380.14%). These trends are consistent with, and numerically greater than, their counterparts from the larger sample of

participants who completed the study. Specifically, for participants who completed the study, average error_{portals} and average error_{time} improved 671% and 129%, respectively. Accordingly, the non-significant ANCOVAs likely reflected low power (given the matched participant sample size) as opposed to an outcome that would truly lead to a different conclusion than was drawn from participants who completed the study.

Second, one-sample *t*-tests determined whether sums of self-regulated learning processes were significantly greater than zero to determine whether matched participants verbalized all of the self-regulated learning processes. One-sample *t*-tests indicated that the sum of task analysis, $t(9) = 16.16, p < .001, d = 5.11$, self-motivation beliefs, $t(9) = 6.35, p < .001, d = 2.01$, monitoring, $t(9) = 9.41, p < .001, d = 2.98$, control, $t(9) = 12.17, p < .001, d = 3.85$, and self-judgment, $t(9) = 4.35, p = .002, d = 1.38$ were all significantly greater than zero. Self-reaction, $t(9) = 2.18, p = .06, d = 0.69$, was not significantly greater than zero.

Table 13

Sums, means, and standard errors of micro self-regulated learning processes.

Micro Process	Sum	Mean (SE)
Task Analysis	1989	198.90 (12.31)
Self-Motivation		
Beliefs	163	16.3 (2.56)
Monitor	2715	271.50 (28.84)
Control	1324	132.40 (10.88)
Self-Judgment	54	5.4 (1.24)
Self-Reaction	11	1.10 (.50)

These results suggested that participants who did not complete the study would have verbalized all but one of the self-regulated learning processes (i.e., self-reaction) that are described by Zimmerman's (2000, 2002, 2011) and Pintrich's (2000, 2004) models of self-regulated learning had they completed the study. It is important to note, though, that the self-reaction mean was 1.10. That average suggested that matched participants verbalized self-reaction processes

albeit not frequently. In addition, that average is very close to the self-reaction mean associated with the larger sample of participants who completed the study ($M = 1.14$). It is also important to note that the t -test that examined the frequency of self-reaction processes in the larger sample of participants who completed the study was not close to the criterion that separated significant from non-significant, $t(64) = 5.77, p < .001, d = .72$. Taken together, these facts suggested that the frequency of self-reaction processes would still have been statistically significant even if participants who did not complete the study had done so and their data were analyzed along with the data from the participants who completed the study. Accordingly, it is unlikely that attrition would have led to a different conclusion regarding whether participants verbalized all of the self-regulated learning processes.

Third, the lag 1 and lag 2 transitional probabilities between macro self-regulated learning processes and their corresponding z-scores are presented in the transitional diagrams in Figures 9 and 10, respectively. In the transitional diagrams, thick and thin lines indicate significant and non-significant transitions, respectively.

Figure 12. Lag 1 transitional probabilities (top) and z-scores (bottom) of the macro self-regulated learning processes. Note: One-tailed, $*p < .001$

Figure 13. Lag 2 transitional probabilities (top) and z-scores (bottom) of the macro self-regulated learning processes. Note: One-tailed, $*p < .001$

Results indicated that, for the lag 1 and lag 2 transitions, only transitions between a macro self-regulated learning process and itself were significantly greater than their expected probabilities (i.e., dependent) with the exception of the self-reflection to self-reflection lag 2 transition. All other transitions were not significantly greater than their expected probabilities (i.e., independent). Therefore, it is likely that participants who did not complete the study would not have self-regulated their learning in the cyclical manner suggested by Zimmerman (2000, 2002, 2011) if they had completed the study.

APPENDIX B

EXPANDED LITERATURE REVIEW AND HISTORICAL FOUNDATIONS

CHAPTER I

SIMULATIONS

It is the duty of the Department of Defense (DoD) to train US soldiers in the knowledge and skills that will be used in situations related to defense and national security. However, there are an unlimited number of situations to train for that range in both stress and complexity (Fletcher, 2009). Many of those situations are not readily available or are too dangerous to experience in real life (Mantovani, 2001). Therefore, the DoD often trains soldiers for these complex and stressful situations by means of simulation (Fletcher, 2009).

The DOD defines a simulation as the implementation of a model, which represents a system, process, entity or phenomenon, in order to show how it operates over time (DoD, 1998). For example, there is a model, or process, of how to clear a building, which involves the following activities: (1) securing the perimeter, (2) entering a building, (3) seizing or firing on enemy targets, (4) and rescuing bystanders and casualties (Phillips, McDermott, Thordsen, McCloskey, & Klein, 1998). A simulation of clearing a building would allow trainees to see how

these activities are performed or allow trainees to perform these steps in the process.

Types of Simulations

The DoD classifies simulations into three separate categories: live, virtual, and constructive (DoD, 1998). First, a live simulation illustrates a model by means of real people using real equipment within a collocated environment. This way, trainees can acquire both declarative and procedural knowledge of the real equipment within a real context. For example, trainees are able to learn both what the controls and gauges of a tank look like as well as how to proficiently drive it through a real environment. Second, a virtual simulation illustrates a model by means of using fabricated equipment, people, environments, or some combination thereof. Again, trainees are able to acquire declarative and procedural knowledge of fabricated equipment within fabricated environments. For example, trainees are still able to learn both what the controls and gauges of a tank look like as well as how to proficiently drive the tank, even though the tank and the environment may not be real. Third, a constructive simulation illustrates a mathematical, decision-making, or statistical model of a system by which people input conditions into the model and the system simulates the outcome.

In these cases, trainees are acquiring only declarative knowledge, such as cause-and-effect relationships.

Table 1

Types of simulations adapted from Petty (2007.)

Category		Trainees	Systems	Knowledge
Live		Real	Real	Declarative & Procedural
Virtual	Hybrid	Real	Simulated; physically constructed & computer-generated	Declarative & Procedural
	PC-based	Real	Simulated; computer-generated	Declarative & Procedural
Constructive		Simulated	Simulated	Declarative

As indicated in Table 1, live and virtual simulations allow trainees to acquire both declarative and procedural knowledge while interacting with real or fabricated systems, respectively. For example, a live simulation could involve trainees learning how to shoot a real gun and a virtual simulation could involve trainees learning how to shoot a fabricated gun. In either instance, trainees are learning knowledge concerning facts about the guns as well as knowledge of how to operate them. In contrast, constructive simulations consist of fabricated agents interacting with fabricated systems. For example, a trainee would input

factors, such as distance from target and target speed, into the constructive simulation. In return, the simulation would output the probability that the target would be hit. Therefore, trainees are not learning procedural knowledge of how to shoot the gun; instead, trainees are learning declarative knowledge about the cause-and-effect relationships of gun parameters and outcomes. Given the limitations of what can be learned within a constructive simulation, only live and virtual simulations will be discussed in greater detail.

Live Simulations. As briefly described, live simulations involve real-life, hands-on military exercises, drills, and missions taking place in a realistic setting (Prensky, 2002). Therefore, trainees may be required to practice real tasks, such as shooting live weapons, driving tanks, or flying air vehicles. Depending on the training task, these exercises could require the attendance of a small number (e.g., 5) or a large number (e.g., 10,000) of trainees.

Live military simulations have proven to be neither completely efficient nor effective for the following reasons (Kennedy, 1999). First, there is a potential danger associated with practicing on a real piece of equipment or vehicle that is unfamiliar to the trainee. Mistakes while operating the equipment may be harmful to the trainee, destructive to the equipment, or both. Second, there is a great monetary cost associated with live simulations. In particular, the National

Training and Simulation Association (NTSA) estimated that the cost of flying a fighter aircraft is at least \$5,000 per hour, driving a tank is at least \$75 per mile, and flying a helicopter is at least \$3,000 per hour. Third, there is a limited amount of time to practice with live equipment. Due to the limited availability of equipment, cost of operating the equipment, the need to accommodate the training of a large number of trainees, and individual learning differences among trainees, not every trainee will receive the amount of practice required for them to learn. Overall, because live simulations can be dangerous, expensive, and an inadequate source of practice, they may not always be the best training solution.

Virtual Simulations. The DoD has attempted to circumvent the problems with live simulations by supplementing them with virtual simulations (Prensky, 2002), which do not involve the use of real equipment or real environments. Instead, virtual simulations consist of mock-ups of equipment, environments, or both that are physically constructed, computer-generated, or both (Caro, 1988; DoD, 1998). Most virtual simulations fall into two categories: hybrid virtual simulations and PC-based virtual simulations.

Hybrid virtual simulations consist of both physical and virtual components. For example, a hybrid virtual flight simulation could consist of a physical mock-up of

an aircraft in conjunction with an interactive, computer-generated representation of gauges and the view of the outside world.

There are several benefits associated with hybrid virtual simulations. First, in comparison with using real equipment, using mocked-up equipment reduces the risk of trainees harming themselves or damaging real equipment. Second, trainers are able to easily customize the graphics and scenarios experienced by the trainees because the representations are computer generated. Interacting with physical equipment and computer-generated views of the environment, such as with the case of the flight simulator, allows trainees to acquire and practice applying the cognitive skills (e.g., coordination, decision-making, & planning) and motor skills required before entering a live environment (Baxter, Harris, & Phillips, 2004; Baxter, Ross, Phillips, Shafer, & Fowlkes, 2004; Matthews, 2010). Third, because the scenarios are not real, trainees have the ability to practice the same scenario longer and more often than they would during a live simulation.

Despite those benefits, however, hybrid virtual simulations have three shortcomings. First, although they are less expensive than live simulations, hybrid virtual simulations can still be expensive. For example, Smith (2007) suggested that a single hybrid virtual simulation may cost within the range of \$20,000 to

\$50,000. Second, because of the expense, trainees will have access to a limited number of hybrid virtual simulations. Thus, trainees will have to take turns using this equipment. Third, because trainees have to take turns using this equipment, there are still constraints associated with the amount of time a trainee is able to practice. To accommodate other trainees, facilitators, or hours-of-operation, hybrid virtual simulations may not be accessible for the amount of time needed for a trainee to learn the necessary knowledge and skills.

These shortcomings have prompted the DoD toward the adoption of another type of virtual simulation, the PC-based virtual simulation. PC-based virtual simulations consist of strictly computer-generated equipment and environments that a trainee would access using a personal computer (PC). PC-based virtual simulations include off-the-shelf games (e.g., *America's Army*), as well as more configurable virtual environments (e.g., *Virtual Battlestation 2*; *VBS2*). Smith (2007) offered the following advantages of PC-based virtual simulations.

First, the capabilities of PC-based virtual simulations are advanced. For example, current PC-based virtual simulations are capable of creating virtual training environments that are high in fidelity, that is, the extent to which the virtual simulation emulates the real world, both physically and psychologically.

For example, many PC-based virtual simulations have embedded 3D gaming and physics engines that create accurate models of real geographical locations (Smelik, Tutenel, de Kraker, & Bidarra, 2010) and realistic human-like movements and interactions (Mann, Lyons, & de la Cruz, 2008). These models allow trainees to prepare for what a particular terrain looks like and how a trainee would be able to interact with that environment before traveling to the physical geographical location. In other instances, many PC-based virtual simulations can appear and respond realistically enough to mimic real life distributed command-and-control situations (Cooke & Fiore, 2009). For instance, trainees could train to operate uninhabited air vehicles (UAVs) and emergency response communications using the same user interface that would be used in real life.

Second, the overall effectiveness of PC-based virtual simulations has been supported through many years of research and practical experience (Vogel, Vogel, Cannon-Bowers, Bowers, Muse, & Wright, 2006). Specifically, in a meta-analysis of 32 studies, Vogel et al. (2006) found that computer-based simulations produced higher reported performance and more positive attitudes than traditional training methods. Similarly, PC-based virtual simulations have shown to be effective within several domains such as corporations (Heiphetz & Woodill,

2009), higher education (Wankel & Kingsley, 2009), and medicine (Boulos, Hetherington, & Wheeler, 2007).

Third, the low cost of PC-based training environments have made them more accessible than more expensive simulators. For example, a single PC equipped with virtual simulation software may cost less than \$5,000, whereas a comparable hybrid virtual simulation might cost up to \$50,000 (Smith, 2007). Due to the dramatic reduction in cost, PC-based virtual simulator software can now be installed directly within PC labs, installed on trainees' personal computers, or accessed through the Internet. Given increased accessibility, trainees now have the ability to extend the amount of time they have to practice. In many instances, PC-based virtual simulations allow trainees to practice on their own during their free time, thus eliminating the time-restrictions associated with sharing equipment, simulation facilities, and facilitators.

Summary

Live simulations, hybrid virtual simulations, and PC-based virtual simulations all give trainees the ability to understand and interact with a model of a process or phenomenon that occurs over time. Each of these simulations differ in regard to how accessible they are to the trainees. For example, simulations that are the least accessible offer trainees the least amount of time to practice the

learning task, whereas simulations that are the most accessible offer trainees the most time to practice the learning task. Given the constraints associated with using real equipment, live simulations offer the least accessibility and time for trainees to practice. In contrast, PC-based virtual simulations offer the most accessibility and time for trainees to practice. Specifically, PC-based virtual simulations even allow trainees the flexibility to practice on their own during their free time.

The concept of "practicing on one's own" is accompanied by motivational and cognitive processes that are different than practice that is externally facilitated by instructors. In Chapter II, I will discuss the concept of "self-regulated learning," a process which describes how learners practice on their own. For the most part, self-regulated learning has been studied within the realm of academic learning. However, in Chapter III, I will discuss how self-regulated learning has been studied, albeit limitedly, within PC-based virtual simulations.

CHAPTER II

SELF-REGULATED LEARNING

In academic learning environments, students often have to practice and complete learning tasks on their own. In addition, students have to know that they have adequately practiced or have completed these learning tasks. For example, students are required to study for tests, read books, and complete homework assignments. In completing these tasks, the students must also understand if they have learned all of the necessary information for the test, comprehended what they read, and completed their homework correctly.

Researchers in the education domain refer to the processes that occur during these activities as self-regulated learning, which refers to the "processes whereby learners personally activate and sustain cognitions, affects, and behaviors that are systematically oriented toward the attainment of personal goals" (Zimmerman & Schunk, 2011). During this process, learners attempt to reduce the discrepancy between the learning goals and their current learning performance by adapting their cognitions, affects, and behaviors to the requirements of the learning task.

Self-directing one's cognitive processes requires metcognitive processes (Pintrich, 2000; Zimmerman, 2000). Flavell (1979) described metacognition as our cognition about our cognitive processes.

There are three different ways in which metacognition occurs. First, we possess knowledge about our cognitive processes. Second, we are able to actively monitor cognitive processes. Third, we are able to control our cognitive processes. For example, we can possess knowledge of, monitor, and control several facets of cognition, such as memory (Dunlosky, Serra, & Baker, 2007), comprehension (Dunlosky & Lipko, 2007), attention (Loper & Hallahan, 1982), and decision-making (Cohen, Freeman, & Wolf, 1996).

Theories of Self-Regulated Learning

There is no single theory of self-regulated learning. Rather there are multiple learning theories that incorporate an explanation of how learners self-regulate. The two most common theories of self-regulated learning stem from the social cognitive theory (Pintrich, 2000, 2004; Schunk, 2001; Schunk & Usher, 2011; Zimmerman, 2000) and the information processing theory (Winne 2001; Winne & Hadwin, 1998, 2008). Despite the conceptual and paradigmatic differences, both theories overlap substantially (Wolters, 2010). Therefore, further discussion of self-regulated learning will involve only the most predominant individual models of self-regulated learning, which are derived from social cognitive theory.

Social cognitive theory. Before describing the conceptual models of the social cognitive theory of self-regulated learning, it is first important to describe social cognitive theory. Social cognitive theory (Bandura, 1986) describes how learners acquire knowledge, skills, strategies, etc. through their reciprocal interactions with and observations of others and the environment. Specifically, social cognitive theory has three central assumptions.

First, "people are viewed as self-organizing, proactive, self-reflecting, and self-regulating rather than reactive organisms shaped by their environmental forces or driven by concealed inner impulses. They are both products and producers of their own inner impulses and their social systems." (Parajes, 2008). That is, human functioning is comprised of reciprocal interactions among (1) personal factors, such as cognition and self-beliefs, (2) behavior, and (3) one's environment (Bandura, 1986; Parajes, 2008; Schunk, 2001). Therefore, all three dimensions affect and are affected by the other dimensions. For example, one's perceived ability to do math (i.e., personal factor) and previous high school level math experience (i.e., environment) influences college-level math performance (i.e., behavior) (Pajares & Miller, 1994). Similarly, experiencing poor math performance now (i.e., environment) will affect one's motivation (i.e., personal

factor) to engage in math-related tasks (i.e., behavior) in the future (Zimmerman, 2011).

Second, learners acquire knowledge and skills by either enactive learning or vicarious learning. Simply put, enactive learning is "learning by doing" and experiencing the related consequences (Schunk, Pintrich, & Meece, 2008). In situations when enactive learning is not possible, learners can partake in vicarious learning, which allows learners to acquire knowledge and skills by observing the actions and consequences of live models (e.g., viewing people in person) , symbolic models (e.g., viewing people or fictional characters on TV), or print models (e.g., reading an instruction manual). However, learning primarily through vicarious learning may result in the acquisition of incomplete skills or knowledge. Despite the mode of learning (i.e., enactive vs. vicarious), learners will be more motivated to reuse the knowledge and skills that result in positive outcomes.

Third, it is possible that previously learned knowledge and skills may not be demonstrated at the time of learning (Rosenthal & Zimmerman, 1978; Schunk, Pintrich, & Meece, 2008). In other words, a learner may acquire knowledge through enactive or vicarious learning, but not translate that knowledge to behavior until the time is appropriate. According to social

cognitive theory, an appropriate time would be when the behaviors fit the task requirements and the outcome of the behavior is likely to be positive. At this time, the learner will be motivated to exhibit the learned behavior. For example, a learner may vicariously learn a strategy of studying vocabulary words at a time when the learner is solving math problems. That strategy is unlikely to be successful in the case of solving math problems. Therefore, the learner will remain unmotivated to use that strategy until the learner is learning vocabulary words.

Model of Social Cognitive Theory of Self-Regulated Learning

Within the social cognitive theory of self-regulated learning, the two most commonly cited models are from Zimmerman (2000, 2002, 2011) and Pintrich (2000, 2004). These two models contain processes that are similar but describe interactions among these processes differently (Wolters, 2010). Table 2 shows the three basic self-regulated learning phases discussed by Zimmerman (2000, 2002, 2011) and Pintrich (2000, 2004): forethought, performance, and self-reflection. Contained within each phase are individual self-regulated learning processes.

Table 2

Self-regulated learning processes combined from Zimmerman (2000, 2002, 2011), Pintrich (2000, 2004), and Wolters (2010).

Forethought	Performance	Self-reflection
Task Analysis	Monitoring	Self-Judgment
Perceptions of Task & Context	Metacognitive monitoring	Self-evaluation
Goal Setting	Monitoring of Motivation and Affect	Causal Attribution
Assessing Prior Knowledge	Monitoring of Performance and Progress	Self-Reaction
Assessing Metacognitive Knowledge	Self-observation of behavior	Affect / Self-satisfaction
Strategy Planning	Self-questioning	Adaptive or Defensive Reactions
Self-Motivation Beliefs	Control	
General motivation	Strategy Selection and Adaptation	
Self-efficacy	Resource Allocation	
Outcome Expectations	Increase or Decrease Effort	
Task Interest	Increase or Decrease Persistence	
Goal Orientation	Seeking Help	
Task Value		

Forethought phase. In the forethought phase, learners engage in two overarching processes: task analysis and the assessment of self-motivation beliefs. Following is a description of both processes.

During task analysis processes, learners first assess the learning task and context and set goals to accomplish the learning task. The learner can set multiple levels of goals. At the highest level are outcome goals, which specify what should be achieved once the learning task has been completed. Within outcome goals can be sub-goals, which specify more proximal outcomes that should be accomplished en route to the outcome goals.

Following goal setting, the learner plans strategies to accomplish the goals. Strategies include ways to guide cognition, affect, and behavioral execution (Pressley & Woloshyn, 1995; Zimmerman, 2011). Planning appropriate strategies relies on activating prior knowledge and metacognitive knowledge (Pintrich, 2000). On one hand, activating prior knowledge involves the searching of memory for declarative and procedural knowledge that is relevant to the learning task. On the other hand, activating metacognitive knowledge involves identifying declarative and procedural knowledge specifically about various facets of cognition (Flavell, 1979). According to Flavell (1979), learners can possess metacognitive knowledge about the learning task, their cognitive strategies, and their cognitive capabilities. First, learners have metacognitive knowledge about the nature of a task. For example, if learners are reading a description about how to do something, they may be able to understand if there is or is not sufficient

information available. In addition, learners can possess knowledge about the organization, redundancy, trustworthiness, and difficulty of the material. Second, learners possess metacognitive knowledge about their own cognitive strategies (Flavell, 1987). That is, based on the characteristics of the learning material, learners are able to make a decision about what cognitive strategy to employ, how to employ it, and when to employ it (Pintrich, Wolters, & Baxter, 2000). Third, learners possess metacognitive knowledge about the capabilities of their own and other's cognitive processes. In regard to learning, some may believe that they learn best by reading a written description, whereas others may believe that they learn best by watching a demonstration.

In conjunction with task analysis processes, learners assess their self-motivation to initiate their identified strategies (Zimmerman, 2011). Learners with high motivation are likely to exhibit increased attention to the learning task, increased choice of completing the learning task, increased effort put into the learning task, and increased persistence in completing the learning task.

As a part of general motivation, learners must also assess their self-efficacy, their outcome expectancy, their task interest, the task value, and their goal orientation. These constructs are sources of general motivation (Zimmerman, 2011).

First, self-efficacy is expectation about one's personal capabilities to perform specific actions (Bandura, 1997; Zimmerman, 2011). Learners with high self-efficacy believe that their actions will result in their preferred outcome and, in turn, will be more motivated to produce those actions (Bandura, 1986; Parajes, 2008). However, learners with low self-efficacy will believe that their actions will not produce a preferred outcome and, thus, will be less motivated to act.

Second, outcome expectancy is the expectation of the results of one's actions. As previously discussed, social cognitive theory posits that learners will not be motivated to execute learned behaviors until they expect a positive outcome (Zimmerman, 2011). Therefore, learners with a positive outcome expectancy tend to have a high motivation to execute a behavior. However, learners with a negative outcome expectancy tend to have low motivation to execute a behavior.

Third, interest has been described as the liking of and willingness to engage in an activity (Schraw & Lehman, 2001). Learners who have an interest in a learning task tend to be motivated to engage themselves in it. However, learners who do not have an interest in a learning task tend to be unmotivated to engage in it.

Fourth, perceptions of task value involve the extent to which the learner believes that the learning task is relevant, useful, and important (Eccles, 1983; Pintrich, 2000). Learners who perceive a high value in the learning task are more motivated to engage in the learning task and re-engage at a later time (Wigfield, 1994; Wigfield & Eccles, 1992) than those who perceive a low value in the learning task.

Fifth, goal orientation is the learners' rationale for completing the learning task. Learners' goal orientation will affect the extent to which learners will be motivated to engage in the learning task (Pintrich, Wolters, & Baxter, 2000). Specifically, there are two main goal orientations: mastery and performance. On one hand, having a mastery goal orientation suggests that the learner intends to deeply understand the learning task and focus on self-improvement (Dweck, 1986; Dweck & Leggett, 1988; Vandewalle, 1997). Learners who possess a mastery goal-orientation tend to be motivated to complete the learning task. On the other hand, having a performance goal orientation suggests that the learner intends to complete the task in order to either gain favorable judgments (i.e., performance-approach) from others or avoid negative judgments from others (i.e., performance-avoid) (Bell & Kozlowski, 2010; Pintrich, Wolters, & Baxter, 2000). Learners who possess a performance goal-orientation have been

suggested to be less motivated than learners who possess a mastery goal-orientation (Bell & Kozlowski, 2010).

In sum, the purpose of the forethought phase is to analyze the learning task to assess motivation to complete the task. During the task analysis, learners assess requirements of the task, set appropriate learning goals based on the requirements of the task, and plan strategies to accomplish those goals. In addition, learners assess their motivation and related motivational sources to execute the strategies.

Performance phase. The performance phase consists of two overarching processes: monitoring and control (Pintrich, 2000; Wolters, 2010; Zimmerman, 2000; 2002; 2011). On one hand, monitoring refers to the learners' efforts to maintain awareness of their motivation, cognitive processes, and progress toward their goal achievement (Pintrich, 2000, 2004; Wolters, 2010; Zimmerman, 2000, 2010). On the other hand, control refers to the management and modification of their motivation, cognitive processes, and strategies used to achieve their goals.

The monitoring and control of cognitive processes (e.g., learning processes), otherwise known as metacognitive monitoring and metacognitive control (Dunlosky & Metcalfe, 2009; Nelson & Narens, 1990), are an important

aspect of self-regulated learning. Respectively, they answer the questions "Am I learning?" and "How do I maintain my learning?"

Figure 1. Model of metacognition adapted from Nelson and Narens (1990)

Nelson and Narens (1990) described the roles and relationships between metacognitive monitoring and metacognitive control within their model of metacognition. As seen in Figure 1, the Nelson and Narens (1990) model of metacognition is comprised of two main components. First, the object level of cognition contains the cognitive processes that are regularly used to complete a task. For example, these cognitive functions could be learning, attention, comprehension, remembering, decision-making, etc. Second, the meta-level of cognition consists of an overarching model of how learners employ their cognitive processes. The meta-level includes pre-existing metacognitive knowledge as well as other knowledge learners obtain while regulating their cognitive processes. For example, learners develop and make changes to the strategies used while studying for a test. Learners may know that they are able to

effectively learn vocabulary words by using flashcards to study. However, learners may additionally learn that using flashcards is not effective for everything they may wish to study. This metacognitive knowledge is stored within the meta-level model.

Information about the effectiveness of the real-time cognitive processes must be transferred from the object level to the meta-level. Similarly, information about how to employ upcoming cognitive processes must also be transferred from the meta-level to the object level. This flow of information is accomplished through metacognitive monitoring and metacognitive control.

Metacognitive monitoring updates the meta-level model based on judgments that learners make about the state of their cognitive processes within the object level. There are two different types of monitoring activity: retrospective and prospective (Vu, Hanley, & Strybel, 2000). Retrospective monitoring refers to the judgments made about cognitive activity that occurred in the past (e.g., "I believe that I have learned everything I need to for the test") whereas prospective monitoring refers to judgments about future cognitive processes (e.g., "I think that this upcoming test will be easy to study for"). Metacognitive monitoring judgments update the model within our meta-level of cognition.

Alternatively, there are instances when learning goals and sub-goals are not being met. Reasons for this are likely to be the inadequate use of cognitive processes or strategies. In such cases, the learner would make adjustments to the strategies in real-time, choose a new strategy, or alter the effort and persistence in executing the cognitive strategy. This management of ongoing cognitive activity occurring within the object level is called metacognitive control (Nelson & Narens, 1990). Specifically, there are five types of metacognitive control (Pintrich, 2000; Pintrich, Wolsters, & Baxter, 2000). First, learners engage in strategy selection and adaptation. Second, learners increase or decrease their effort and persistence in achieving learning goals. Third, learners engage in resource (e.g., time, effort, etc.) allocation. Fourth, learners engage in the regulation of their motivation, emotions, and surrounding environment. Fifth, learners choose when to seek help. For example, learners will make the decision to terminate studying, continue studying, or change the studying strategy based on the outcome of metacognitive monitoring (Dunlosky, Serra, & Baker, 2007). Similarly, learners may choose to focus studying on particular material if they are running out of time.

Self-reflection phase. In the self-reflection phase, learners make self-judgments and self-reactions based on the outcomes of their learning strategies

in the performance phase (Zimmerman, 2011). When making self-judgments, learners are specifically evaluating their performance and making causal attributions to their performance outcomes. In other words, after completing a learning task, learners evaluate their performance against an internal standard. Then, learners attribute the success or the failure of their performance to themselves or an uncontrollable cause. For example, if the learners evaluate their performance as being poorer than the performance standard, then the learner may attribute the failure to their lack of ability or choosing an inappropriate strategy. In contrast, if learners evaluate their performance as exceeding the performance standard, then the learner may attribute the success to their ability in choosing an appropriate strategy. Thus, this strategy will be associated with having a positive expectancy outcome and will be stored for later use.

Following, learners self-react to their performance in two ways. First, learners assess how satisfied they are with their performance. The extent to which the learner is satisfied with their performance produces a negative to positive affective reaction. Second, learners combine their causal attributions and their self-satisfaction and adopt either an adaptive or defense inference. Adaptive or defensive inferences are conclusions that learners make about either altering their future approaches or not altering their approaches, respectively.

For example, if learners attributed their performance to controllable causes (e.g., poor strategies) and feel positively about their performance, then they are more likely to adopt an adaptive inference. These learners are likely to decide to attempt similar tasks again. However, if learners attributed their performance to uncontrollable causes (e.g., poor ability) and feel negatively about their performance, then they are most likely to adopt a defensive inference. These learners are likely to feel helpless or avoid completing similar learning tasks. Consequently, self-reflections affect the learners' interest, self-efficacy, outcome expectancies, and motivation for similar tasks in the future (Zimmerman, 2011). Positive self-reflections would improve those feelings, whereas negative self-reflections would diminish them.

Summary. Social cognitive theories of self-regulated learning share three basic phases: (1) a forethought phase, (2) a performance phase, and (3), a self-reflection phase (Zimmerman, 2000; Pintrich, 2004). In the forethought phase, learners analyze the learning task, set task-appropriate goals, and plan strategies for accomplishing the goals. In the performance phase, learners monitor their performance and regulate their strategies. In the self-reflection phase, learners evaluate whether they met their goals. If the goals were not met and the learners have adopted an adaptive inference and a positive affect, then they would be

more motivated to attempt the task again. However, if the learners have adopted a defensive inference and a negative affect, then their motivation to attempt the task again would be reduced.

The Nature of Self-Regulated Learning

Even though the phases and processes that comprise Zimmerman's (2000; 2002; 2011) and Pintrich's (2000, 2004) models of self-regulated learning are similar, the flow in which these phases and processes functions differs between the two models. Zimmerman (2000, 2002, 2011) stressed that self-regulated learning is meant to be cyclical in nature. Specifically, at the beginning of a learning task, learners will engage in forethought activity (i.e., assessing the task and assessing motivational beliefs). Following, learners will engage in performance activity (i.e., implementing, assessing, regulating, and changing strategies to complete the goal). Lastly, learners will engage in self-reflection activity after completing the learning task (i.e., judge and react to their performance). The learners' causal attributions and affective state will then affect the future forethought activity, thus continuing the cycle. However, Pintrich (2000, 2004) asserted that self-regulated learning is less structured. Instead, the order in which learners exhibit self-regulated learning is flexible and non-linear. Learners adapt their self-regulation approach to the learning task at hand.

Regardless of the differences between the two models, both Zimmerman and Pintrich would agree that self-regulated learning develops with experience. That is, learners are not pre-programmed to self-regulate their learning as described in their models. Instead, learners with different degrees of experience are unlikely to exhibit all self-regulated learning processes in the same frequencies or in the same order (Zimmerman, 2002). For example, differences in the use of self-regulated learning processes have been observed between learners who are new to a task and those who have experience with the task, such as with novices and experts (Schoenfoeld, 1987; Cleary & Zimmerman, 2001). Specifically, differences have been observed primarily in the forethought and performance phases (Cleary & Zimmerman, 2001; Zimmerman, 2000, 2002; Schoenfeld, 1987). For example, those with less experience are less likely to strategize and monitor as effectively. There are two possible explanations for this. First, poor forethought activity could be the result of learners lacking the metacognitive knowledge typically acquired from previous experience. That is, if learners have little or no previous experience, then they do not have the knowledge of strategies and their respective outcomes. Second, inexperienced learners may not know how to monitor their processes and performance when they do not understand a new, complex task. This results in disorganized

monitoring efforts (Zimmerman, 2000). However, with increased experience and persistence, one's ability to self-regulate their learning should improve.

Measuring Self-Regulated Learning

There are two categories of methods for measuring self-regulated learning. These two categories differ in respect to the sensitivity of the measure. At the least detailed level of granularity, self-regulated learning can be measured as an aptitude, e.g., a single, final score aggregated across multiple dimensions or events. Examples of this are self-report questionnaires, structured interviews, or teacher/facilitator judgments. At the most detailed level, self-regulated learning can be measured as an event, e.g., an analysis of the processes one uses to self-regulate, monitor, and control over a period of time (Winne & Perry, 2000). Examples of measuring self-regulated learning as an event are the verbal protocol, error detection tasks, trace methods, and performance observation (Winne & Perry, 2000).

Certain ways of measuring self-regulated learning are employed more often than others. Two common practices are self-report and verbal protocol (Winne & Perry, 2000). The following will describe those measures in detail.

Self-report. Self-report measures are the most frequently used measures of self-regulated learning and related metacognitive constructs (Winne & Perry,

2000). This is most likely due to their ease of administration and their ability to provide access into a learner's unobservable cognitive processes (Kirwan & Ainsworth, 1992).

Self-report measures are able to capture self-regulated learning and metacognition as an aptitude as well as an event. First, when measuring self-regulated learning as an aptitude, there are two commonly used self-report questionnaires: the Learning and Study Strategies Inventory (LASSI; Weinstein, Schulte, & Palmer, 1987) and the Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich, Smith, Garcia, & McKeachie, 1991). The purpose of both measures is to assess the general learning and study strategies employed by college students. However, neither measure assesses real-time self-regulated learning. Rather, both aggregate ratings made about the students' general strategies (i.e., LASSI) or the strategies used within a specific college course (i.e., MSLQ). Second, when measuring self-regulated learning as an event, more refined measurements are used. For example, self-report measures of metacognitive monitoring require subjects to rate their ease-of-learning (EOL), judgment of learning (JOL), and feeling of knowing (FOK) (Pintrich, Wolters, & Baxter, 2000). EOL, JOL, and FOK are used to measure one's metacognitive

monitoring activity at a moment in time rather than one's overall self-regulated learning ability.

Verbal protocol. Verbal protocols, such as the think-aloud technique, are often used to elicit thoughts, attitudes, and cognitive processes while a learner is performing a task (Kirwan & Ainsworth, 1993; Ericsson & Simon, 1984). In many cases, learners provide verbal descriptions of what they are thinking and doing while they are performing the task, otherwise known as giving concurrent reports. Learners can also provide verbal descriptions of what they are thinking and doing after they performed the task, otherwise known as giving retroactive reports. However, verbal reports that occurred more than one minute after the respective behavior are considered to be less accurate and more misrepresented than concurrent reports (Dominowski, 1998).

There are two specific advantages for using the verbal protocol. First, the think-aloud protocol is able to provide useful information about the participants' motor-responses, decision making, and underlying cognitive processes (Kirwan & Ainsworth, 1992). Second, the think-aloud protocol measures self-regulated learning as an event. Greene & Azevedo (2010) suggested that self-regulated learning should be measured as an event for the following reasons. Measuring self-regulated learning allows researchers to observe self-regulated learning in a

finer level of granularity than aptitude measures. The final level of granularity enables researchers to measure the dynamic nature of self-regulated learning. In addition, measuring self-regulated learning as an event allows researchers to measure data over time. Measuring over time enables researchers to understand how self-regulated learning processes evolve over time.

However, there has been concern that the act of talking about one's actions and thoughts could affect performance. To address this concern, researchers have examined whether different types of verbalizations impact performance (Carrol & Payne, 1977; Dominowski, 1998; Ericsson & Simon, 1984; Johnson & Russo, 1978; Roth, 1965). Results of these studies indicated that verbalizing one's thoughts and actions did not affect performance (Carrol & Payne, 1977; Ericsson & Simon, 1984; Johnson & Russo, 1978; Roth, 1965) because the participant verbalizes direct representations of cognitive processes (Ericsson & Simon, 1984). However, performance was affected when participants were instructed to provide direct verbalizations of their cognitive processes and provide a rationale for them (Berry and Broadbent, 1984, 1987). Therefore, requesting rationale statements during verbalization tasks has been discouraged (Ericsson & Simon, 1984).

CHAPTER III

SELF-REGULATED LEARNING WITHIN PC-BASED VIRTUAL SIMULATIONS

It has been suggested that PC-based virtual simulations can foster self-regulated learning (Cannon-Bowers & Bowers, 2010; Zap & Code, 2009). Zap and Code (2009) offered several reasons for this. First, PC-based virtual simulations are inherently interesting. As discussed in Chapter II, interest is a precursor to the motivation to engage in learning activities (Zimmerman, 2011). Second, interacting with PC-based virtual simulations tends to provoke positive emotions, such as enjoyment and pleasure. Positive affect increases the likelihood that a learner will adopt an adaptive inference (Zimmerman, 2011) and re-engage with the virtual simulation (Garris, Ahlers, & Driskell, 2002). Third, PC-based virtual simulations facilitate both intrinsic and extrinsic motivation. Factors such as interest directly influence intrinsic motivation, whereas positive affect indirectly enhances intrinsic motivation (Ryan & Deci, 2002). Other factors, such as competition, rewards, and acknowledgement enhance extrinsic motivation (Zap & Code, 2009). Fourth, PC-based virtual simulations encourage learners to simultaneously manage and pursue multiple goals. Some of these goals could be completing learning tasks, improving one's skills, or winning competitions. Fifth

and consequently, PC-based virtual simulations encourage metacognitive activity. Specifically, learning tasks within these environments require learners' to activate relevant prior metacognitive knowledge (e.g., strategies) as well as monitor and control strategy execution to achieve multiple goals.

Studies Assessing Self-Regulated Learning within PC-based Virtual Simulations

Despite these claims, only three studies have assessed whether learners self-regulate their learning within PC-based virtual simulations. First, Ford, Smith, Weissbein, Gully, and Salas (1998) assessed the relationship among goal orientation, metacognitive activity, practice strategies, and performance outcomes within the PC-based virtual simulation, TANDEM. Second, Orvis, Horn, and Belanich (2006) assessed factors such as motivation, self-efficacy, goal orientation, and metacognitive activity in relation to performance within the PC-based virtual simulation, America's Army. Third, Nietfeld, Hoffman, McQuiggan, and Lester (2008) assessed the effects of goal orientation and metacognitive monitoring on performance within the PC-based virtual simulation, Crystal Island.

In combination, the results of the three studies indicated the following about self-regulated learning within a PC-based virtual simulation. First, self-efficacy has been shown to positively predict motivation and metacognitive activity (Orvis, Horn, & Belanich, 2006). Second, having a mastery goal

orientation has been shown to positively predict self-efficacy, motivation, metacognitive activity, and satisfaction (Ford et al., 1998; Orvis, Horn, & Belanich, 2006). However, having a performance goal-orientation has been shown to negatively predict self-efficacy and satisfaction. Third, metacognitive activity has been shown to be positively related to performance outcomes (Ford et al., 1998; Nietfeld, Hoffman, McQuiggan, & Lester, 2008). Specifically, participants who reported that they thought they were accomplishing their goal well (Nietfeld, Hoffman, McQuiggan, & Lester, 2008) and participants who reported using more metacognitive activity (Orvis, Horn, & Belanich, 2006) tended to demonstrate increased performance.

Without dispute, Ford et al. (1998), Orvis, Horn, and Belanich (2006), and Nietfeld, Hoffman, McQuiggan, and Lester (2008) have begun to shed some light on self-regulated learning within PC-based virtual simulations. However, the general understanding of self-regulated learning within PC-based virtual simulation is still limited. None of the studies have provided an assessment of self-regulated learning, as described by Zimmerman (2000, 2002, 2011) and Pintrich (2000, 2004), within a PC-based virtual simulation. Table 3 highlights the self-regulated learning processes assessed within the three studies. As indicated, only Orvis, Horn, and Belanich (2006) measured at least one self-regulated

learning process within each of the three phases of self-regulated learning. In contrast, Ford et al. (1998) and Nietfeld, Hoffman, McQuiggan, and Lester (2008) only measured processes within the forethought and performance phases. Unfortunately, none of the studies assessed all or most of the possible self-regulated learning processes across all three phases.

Table 3

Self-regulated learning processes evaluated within PC-based virtual simulations.

Forethought	Performance	Self-reflection
Task Analysis	Monitoring	Self-Judgment
Perceptions of Task & Context	<u>Metacognitive monitoring</u> ^{1, 2}	Self-evaluation
Goal Setting	Monitoring of Motivation and Affect	Causal Attribution
Assessing Prior Knowledge	<u>Monitoring of Performance and Progress</u> ^{1, 2, 3}	Self-Reaction
Assessing Metacognitive Knowledge	Self-observation of behavior	<u>Affect / Self-satisfaction</u> ²
Strategy Planning	Self-questioning	Adaptive or Defensive Reactions
Self-Motivation Beliefs	Control	
<u>General motivation</u> ²	<u>Strategy Selection and Adaptation</u> ^{1, 2}	
<u>Self-efficacy</u> ^{1, 2}		
Outcome Expectations	Resource Allocation	
<u>Task Interest</u> ³	Increase or Decrease Effort	
<u>Goal Orientation</u> ^{1, 2, 3}	Increase or Decrease Persistence	
Task Value	Seeking Help	

Note. The underlined processes were measured within a PC-based virtual simulation

¹ Ford et al. (1998), ² Orvis, Horn, & Belanich (2006), ³ Nietfield, Hoffman, McQuiggan, and Lester (2008)

A Need for More Research

To date, an assessment of self-regulated learning as described by Zimmerman (2000, 2002, 2011) and Pintrich (2000, 2004) has not been completed within a PC-based virtual simulation. Even though one study (i.e., Orvis, Horn, & Belanich, 2006) had measured at least one process within each phase of self-regulated learning, none of the studies had measured a complete model of self-regulated learning within a PC-based virtual simulation. This is problematic because without measuring all of the possible factors included within these models of self-regulated learning, we are unable to determine whether trainees are actually able to self-regulate their learning in the ways that are accepted within the education community (e.g., Zimmerman, 2000, 2002, 2011; Pintrich, 2000, 2004). If learners are not self-regulating their learning as specified by Zimmerman (2000, 2002, 2011) and Pintrich (2000, 2004), it causes concern for the effectiveness of trainees practicing on their own within PC-based virtual simulations. Therefore, further research is required to determine whether learners are self-regulating their learning in accordance to the accepted models and what model of self-regulated learning best describes the processes that the learners exhibit.

Purpose of Current Study

The primary purpose of the current study is to assess whether learners are self-regulating their learning within a PC-based virtual simulation in accordance with either Zimmerman's (2000, 2002, 2011) or Pintrich's (2000, 2004) models of self-regulated learning. To conclude that learners are self-regulating their learning in this way, the following requirements must be met.

First, there must be evidence that learning took place. Depending on the type of learning task, learning can be defined as a relatively permanent change in behavior, knowledge, or skills as a result of experience (Wade & Tarvis, 2004). Observing a change in behavior, knowledge, or skill set requires at least two measurements. Specifically, a measurement must be made before the completion of a learning task and after the completion of a learning task. Otherwise, there is no evidence that behavior, knowledge, or skill changed.

Second, there must be evidence that all three phases of the self-regulated learning model were active at least once during the completion of the learning tasks. This would provide evidence for the validity of Zimmerman's (2000; 2002; 2011) and Pintrich's (2004; Pintrich, Wolters, & Baxter, 2000) models of self-regulated learning. In addition, this would provide evidence for the generalizability of their models to PC-based virtual simulations. However, if fewer than three phases of the self-regulated learning model are active, then there

would be no conclusive evidence that learners are self-regulated their learning in accordance with the models established by Zimmerman (2000, 2002, 2011) and Pintrich (2000, 2004).

Third, there must be evidence that learning is related to changes in self-regulated learning processes. Specifically, increased performance should correlate to the activation of the three self-regulated learning phases. For example, learning should be related to forethought activity, performance activity, self-reflection activity, or combinations of these phases. A failure to demonstrate at least one relationship may suggest that any learning that occurred was independent of self-regulation.

The secondary purpose of the present study is to assess what model of self-regulated learning best describes the processes exhibited by the learners. As discussed in Chapter II, Zimmerman's (2000, 2002, 2011) and Pintrich's (2000, 2004) models of self-regulated learning contain similar components. However, the major difference between their models is the flow of the processes. On one hand, Zimmerman suggested that self-regulated learning phases occur in a cyclical manner, where learners exhibit forethought phase activity, performance phase activity, and self-reflection phase activity, in that order. Then, self-reflection phase activity further affects future forethought activity, thus

continuing the cycle. On the other hand, Pintrich indicated that self-regulated learning processes are adaptive and unstructured. That is, they occur in the order that best fits the task.

To conclude that Zimmerman's model of self-regulated learning best fits processes exhibited by the learners who self-regulated their learning, there must be evidence that the flow between self-regulated learning phases is similar to the flow indicated by Zimmerman (2000, 2002, 2011). Otherwise, it will be concluded that Pintrich's (2000, 2004) model of self-regulated learning best fits the flow of processes exhibited by the learners.

In summary, the current study will be designed to answer two questions. First, are learners self-regulating their learning within a PC-based virtual simulation as described by either Zimmerman (2000, 2002, 2011) or Pintrich (2000, 2004)? Consequently, this question necessitates finding evidence that learning had occurred, that all three self-regulated learning phases were active, and that learning was associated with self-regulated learning processes. Second, what model of self-regulated learning best fits the pattern of processes exhibited by the learners? Consequently, this question necessitates finding evidence that the flow of exhibited self-regulated process was or was not structured as described by Zimmerman (2000, 2002, 2011).

These research objectives are important because trainees are more frequently allowed to practice on their own using PC-based virtual simulations. However, practicing on one's own is suggested to be most effective when learners are exhibiting the self-regulated learning processes described by Zimmerman (2000, 2002, 2011) and Pintrich (2000, 2004). The current study will be the first study to determine whether learners are able to self-regulate their learning in accordance to those models within a PC-based virtual simulation. Additionally, the current study will be the first study to determine what model of self-regulated learning best describes the processes exhibited by the learners.

Overview of Current Study

Participants will be given 2 hours to complete levels 0 through 11 within an off-the-shelf PC-based virtual simulation. During each level, the following data will be recorded. First, participants will be asked to think aloud about what they are doing and thinking. The researcher will transcribe these verbalizations. Second, the amount of time it takes and the number of shots fired will be measured. Once the participants have either completed 12 levels or have played for 2 hours, interaction with the PC-based virtual simulation and recording will cease. At this time, the participants will be debriefed and released.

Following data collection, the researcher will divide the verbalizations into segments of independent clauses. Then, two researchers will code each segment as being one or more of 26 processes within one of the three self-regulated learning phases.

Hypotheses

Overall, it is predicted that participants will self-regulate their learning in accordance to either Zimmerman's (2000, 2002, 2011) or Pintrich's (2000, 2004) model of self-regulated learning. Therefore, this means that the following requirements are predicted to be met. *First, it is predicted that learning will occur between the early and later levels. Second, it is predicted that participants will exhibit processes within all three phases of self-regulated learning by the last completed level of the PC-based virtual simulation. Third, it is predicted that increased learning will be related to higher proportions of some self-regulated learning activity. Conversely, decreased learning will be related to lower proportions of some self-regulated learning activity.*

Despite the prediction that learners will self-regulate their learning as described by either Zimmerman (2000, 2002, 2011) or Pintrich (2000, 2004), there are no specific predictions about what model the processes exhibited by the participants will most closely mirror. Specifically, there are no predictions about

whether processes will be structured in the way described by Zimmerman (2000, 2002, 2011) or lacking that structure as suggested by Pintrich (2000, 2004).