MEASURING SELF-REGULATION IN A COMPUTER-BASED OPEN ONLINE INQUIRY LEARNING ENVIRONMENT USING GOOGLE.

by

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A dissertation submitted to the Graduate Faculty in Educational Psychology in partial fulfillment of the requirements for the degree of Doctor of Philosophy,

The City University of New York

2011

This manuscript has been read and accepted for the Graduate Faculty in Educational Psychology in satisfaction of the dissertation requirement for the degree of Doctor of Philosophy.

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Abstract

MEASURING SELF-REGULATION IN A COMPUTER-BASED OPEN ONLINE INQUIRY LEARNING ENVIRONMENT USING GOOGLE.

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This dissertation investigated the impact of expert-modeling of a self-regulatory strategy in an open online inquiry learning environment (Google) on forty (n = 40) community college students' performance on an online inquiry task, the role of key self-regulatory measures, and calibration (accuracy of performance judgment) during the online inquiry phases searching/evaluating, and synthesizing. Theory-driven data for the study was gathered by employing both microanalytic and trace data methods. The results generally supported the hypotheses and showed that expert-modeling of a self-regulatory strategy helped students to improve performance during the online inquiry phases searching/evaluating and synthesis. In addition, the study showed that the key self-regulatory measures planning, self-efficacy, and attribution were predictive of students' writing scores. A comparison of mean-bias scores as a measure of calibration universally showed that student overestimated their performance at key points during their online inquiry (presentation of task, search completion, essay completion). Self-regulatory strategy instruction, however, helped students in the Expert-Modeling group to significantly better calibrate their performance after the presentation of the task and completion of the essay. The study further showed that students in the Expert-Modeling group entered qualitatively higher search terms and selected qualitatively higher websites for their inquiry. An exploratory analysis of the students' search patterns (self-efficacy and self-evaluation for websites selected for inquiry) showed lower mean variances for

students who received the self-regulatory strategy training during phases searching/evaluating, which is indicative of a more consistent and successful search pattern during their online inquiry.

Acknowledgements

I would like to express my sincere gratitude to Dr. Barry J. Zimmerman who has provided me with his mentorship and guidance over the past five years at the Graduate Center. He has been a wonderful adviser and his scholarly support and feedback will continue to guide me as I move forward with my academic career. It has been an amazing journey and I am truly grateful for everything that Dr. Zimmerman and the Educational Psychology Program have imparted on me. I would also like to express thanks to my dissertation committee members, Drs. Bruce Homer and Bert Flugman, whose constant feedback and advise have helped me to continuously improve my work. Further, I'd like to thank my outside readers, Drs. Peggy Chen and Hefer Bembenutty, who have offered valuable input and suggestions for further research.

As a proponent of social cognitive theory and someone who values the influence of his environment, I am humbled and eternally grateful for having a wonderful network of family and friends, both in New York and my home country Austria. Without their continued and loving support, this milestone would not have been possible. I would like to express my heartfelt appreciation to my loving families in Austria (Danke Mutti und Vati!) and New York (Thank you Mom and Dad!) who were always supportive along the way. A special thank you belongs to my dear mentor and friend Dr. Stuart Schulman, who always believed in me and supported my work and professional development ever since I came to New York some 8 years ago.

Lastly - and most importantly - I thank my beautiful and most wonderful wife Tsedale, whose unconditional caring support and love were my source of nurturing energy that kept me going during this Ph.D. journey. Thank you, Tsedale, I love you!

Table of Contents

List of Tables

List of Figures

CHAPTER ONE

INTRODUCTION

Technological developments and the increased use of the computer and the Internet in education resulted in a series of changes in education in general, and in educational methods and models in particular. Distance learning and online education especially show that we experience a fundamental shift in education and that the roles of teachers and students have changed significantly (Bothma & Monteith, 2004). Learning becomes more student-centered with less teacher interaction, and students need to find new ways of organizing and handling their learning.

Due to the presence of computer-based learning environments (CBLEs) and the Internet, students can access information much faster than in the past. However, this "overwhelming information environment" often makes it difficult for students to engage in meaningful inquiry (Eagleton & Guinee, 2002). Ikpeze and Boyd (2007) even speak of a "knowledge explosion" through the Internet and that learners are challenged to "gather, retrieve, synthesize, evaluate, and transform information." Following the constructivist learning tradition, students need to make the connections and sort out the complexity of information. Linn and Eylon (2006) suggest that it is important to enable students to monitor and evaluate their learning in order to produce a "construction of understanding" (p. 521). Consequently, it must be ensured that students can successfully access resources from the Internet in order to empower themselves to develop knowledge and skills at a more sophisticated level (Rogers & Swan, 2004). Unfortunately, this is not always the case and students face a series of metacognitive challenges during their online inquiry (Quintana, Zhang, & Krajcik, 2005).

CBLEs are widely used in contemporary classroom practices; and the emergence of hypermedia, web-based learning, and other open-ended learning environments have especially triggered a series of issues that need to be addressed by researchers in order to provide strong learning environments for the students (Azevedo, 2005a). Mayer (2003) chiefly argued that any recommendation for practice needs to be grounded in scientific research, which will lead, based on the replication of findings, to the further development and extension of theoretical frameworks. Lajoie and Azevedo (2006) see the necessity in developing a model of self-regulated learning (SRL) that will allow the students to better succeed in these more open-ended learning environments.

Winters, Greene, and Costich (2008) pointed out that "many students fail to take full advantage of CBLEs" (p.429). This holds particularly true for solely web-based inquiry tools, such as Google, which have already been widely adopted in the daily classroom practices. In order to overcome these challenges and to be able to take advantage of the full capacity of these powerful research tools, students need to be taught how to self-regulate their search behaviors. Research on self-regulation and CBLEs suggests that this process can be facilitated through modeling or computer based-scaffolds. However, the results do not give a clear picture of how and when students self-regulate their learning, and what key self-regulatory processes are related to student achievement. This notion has been highlighted in Winters et al.'s (2008) critical analysis about self-regulation of CBLEs. The authors point out that research evidence is still inconclusive about the role self-regulation can play in CBLEs and recommend that future research must focus on the quality of self-regulatory processes in order to determine whether actual behavior is both effective and appropriately applied. In addition, there has been little emphasis on motivational and self-reactive processes, as well as how these SRL processes are linked to actual learning outcomes. In order to better measure SRL in its full diversity, Winters et al. (2008) indicate that traditional self-report measures of SRL, such as questionnaires, do not fully capture SRL processes and recommend that think-aloud procedures (e.g., Moos & Azevedo, 2009a), as well as trace data measures (e.g., Winne, 2006) should be emphasized instead.

Moos and Azevedo (2009b) reviewed literature on computer self-efficacy and highlighted the importance of investigating self-efficacy within different types of CBLEs, as both cognitive and metacognitive demands may vary across environments. Only a few studies looked at process data and how key self-regulatory processes mediate learning in open-ended learning environments, where the learner controls what information is accessed. Similarly to Winters et al. (2008), the authors recommend that future research must focus on the relationship between self-efficacy, learning outcomes and self-regulatory processes.

Computer-based Learning Environments (CBLEs)

Following Winters et al.'s (2008) definition, "CBLEs incorporate various aspects of computer technology to assist individuals in learning for a specific educational purpose" (p. 439). Information may be represented and linked in multiple ways; such as text, diagrams, images, or graphs. These environments may also be called hypermedia environments and cannot be directly manipulated by the user (as opposed to simulations or microworlds). These open-ended learning environments give the learner control over the learning task and allow them to interact with the environment in order to construct their own knowledge. Learners who navigate within these environments in order to access information are required to demonstrate a high level of control and self-regulation (Clarebout & Elen, 2006). While some research on students self-regulation in CBLEs used environments with access to a specific domain or topic (e.g. Azevedo and colleagues used Microsoft Encarta, an online encyclopedia), others used environments with unrestricted access to information by utilizing the World Wide Web (e.g. Rogers & Swan, 2004; Kauffman, 2005).

Online Inquiry

Learners engage in inquiry learning by going through the processes of posing and exploring questions; collecting, interpreting, and synthesizing various forms of data and information; and finally developing an explanation to answer the given questions (National Research Council, 2000).

Online inquiry, as a special form of inquiry, follows similar cognitive processes by (1) posing a research question, (2) searching for information online (e.g. websites, online libraries), (3) evaluating and selecting components of useful information, and (4) coherently integrating components of that information to answer the research question (Quintana et al., 2005). In order to master these online inquiry phases, learners have to demonstrate metacognitive knowledge (knowledge about cognition) and metacognitive regulation (regulation of cognition), as well as motivation (Schraw, 2007). Learners' knowledge about cognition includes knowledge about (1) one's self as a learner, such as ones cognitive abilities; (2) the task at hand, such as the cognitive demands that are required for a task; and (3) strategies in order to solve the task, such as strategies for learning and problem solving. Knowledge about regulation of cognition, on the other hand, involves processes related to goal setting and task planning, executing appropriate strategies to solve a problem, monitoring of whether goals are met, and evaluating one's learning (Schraw, 2007).

Mastering these processes require learners to self-regulate their learning, however, research has shown that this is not always the case (Lajoie & Azevedo, 2006). Azevedo, Green, and Moos (2007) demonstrated that students who were provided with external regulation (human tutors who modeled self-regulatory script) enhanced their learning more than students who relied on internal self-regulation. Schraw (2007) highlights the importance of this study, since self-regulatory scaffolding, through modeling, proved to be more effective for novices than internal self-regulation, which may be specifically attributed to novices' lack of domain knowledge to organize and elaborate new information.

A Social Cognitive View of Self-Regulation

Social cognitive theory is based on the work of Albert Bandura (1986) who explains human function as the reciprocal interaction between behaviors, environmental variables, cognitions and personal factors (Figure 1). These three factors influence each other differentially and may vary across activities, individuals and circumstances. In this view, human functioning is not merely the result of a reactive change to environmental stimuli or inner impulses; rather, through the reciprocal determinism, human change is influenced by cognitive, vicarious, self-regulatory and self-reflective factors. Hence, people are proactively shaping their environment and are in turn, reciprocally shaped by the environment; functioning both as products and producers of their environment. Of central importance to Bandura's theory is the construct of perceived self-efficacy, which refers to beliefs about one's capabilities to learn or perform behaviors at designated levels. Bandura (1986) hypothesized that these beliefs are developed through four types of sources: (1) mastery experiences, which are based on the interpretations of one's previous performance, (2) vicarious experiences (e.g., through observation of models), (3) verbal persuasion (e.g., learners may exert additional effort based on verbal messages they receive), (4) psychological states (e.g., anxiety or stress may lower individuals' beliefs about whether they can do a particular task). Self-efficacy beliefs influence learners' behaviors such task choice, effort, persistence, and achievement; which in turn reciprocally affect learners' self-efficacy (Schunk, 1995). In sum, the triadic processes as outlined by Bandura (1986) are proactively and reactively adapted for the personal attainment of goals.

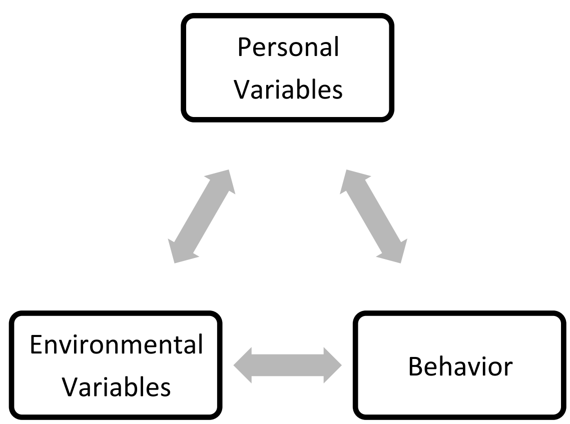
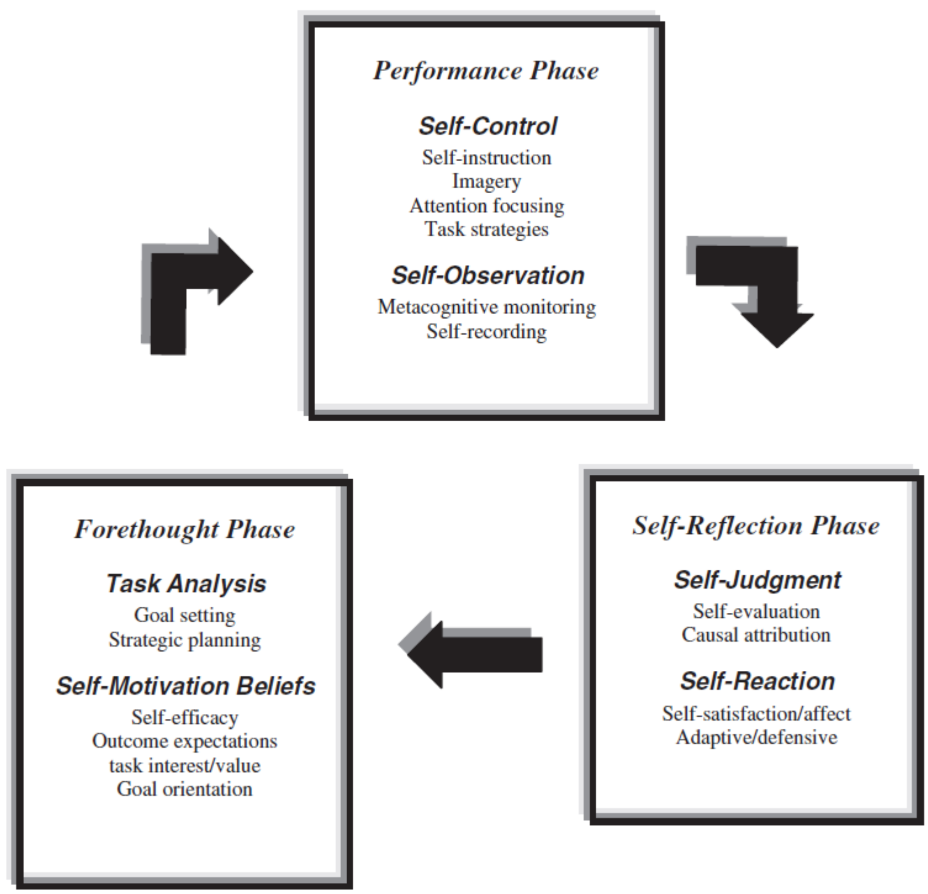


Figure 1. Reciprocal interactions in human functioning

Zimmerman's (1998, 2000) cyclical model of self-regulation (Figure 2), which is based on Bandura's work, highlights the importance of feedback from prior performance in order to be able to make adjustments to one's performance towards the attainment of a desired standard, or goal. These adjustments during learning and performance are necessary and must be monitored during three open triadic feedback loops due to the ever-changing nature of personal and environmental factors.



Phases and subprocesses of self-regulation. From "Motivating Self-Regulated Problem Solvers" by B. J. Zimmerman and M. Campillo, 2003, in J. E. Davidson and R. J. Sternberg (Eds.), The Nature of Problem Solving, p. 239. New York: Cambridge University Press. Copyright 2003 by Cambridge University

Figure 2. Phases and subprocesses of self-regulation

This model explains self-regulation as three cyclical phases (Figure 2); namely, forethought, performance control, and self-reflection: (1) The forethought phase includes influential processes that precede efforts to act and set the stage for it; (2) the performance or volitional control phase includes processes related to the actual performance efforts and affect attention and action; and lastly, (3) the self-reflection phase includes processes that occur after performance efforts and influence a person's response to that experience. During this phase, self-judgment and self-reaction will complete the self-regulation cycle by informing subsequent forethought phases regarding future performance efforts.

CHAPTER TWO

LITERATURE REVIEW

Self-Regulation of Learning in CBLEs

The following section is based on the key findings of a comprehensive review of literature by Winters et al. (2008) about self-regulation of learning in CBLEs. The authors identified a total of 33 empirical research studies that specifically made SRL a key construct for their investigation. The models and frameworks used most in this line of research are related to the work of Pintrich (2000) and Zimmerman (1998, 2000, 2001) from a social cognitive perspective, as well as Winne and Hadwin (1998) from an information processing perspective. These theories involve a series of sequential and cyclical phases. The first phase typically involves processes related to forethought and planning (e.g., task identification, goal setting, strategy elaboration, and self-motivation). In phase two, individuals enact both plans and strategies, while continuously metacognitively monitoring their progress. If during task performance learners detect a discrepancy between their self-set goals and their actual performance, they may execute control processes in order to self-regulate their learning. And lastly, in phase three, learners self-reflect about their learning, which in turn may influence their learning beliefs, beliefs about learning tactics and strategies, as well as the learning context during subsequent self-regulatory cycles.

Both Pintrich (2000) and Zimmerman (2001) identified a series of common underlying assumptions in order to determine and define self-regulated learners. Firstly, self-regulated learners are cognitively, motivationally, and behaviorally active and constructive participants in their learning process. Secondly, self-regulation is a cyclical process during which learners monitor and evaluate their learning progress based on self-set goals, criterion or standards. This process takes place during a cyclical recursive feedback-loop during learning. Thirdly, students exercise control over when and how they engage in a particular learning task; including their choice over self-regulated processes, strategies, or responses. And lastly, biological, contextual and environmental factors play a role in terms of how well students are able to self-regulate their learning and performance.

Pintrich (2000) developed a taxonomy to organize research on self-regulation by focusing on the phases and areas of self-regulation. These phases are comprised of task identification and planning, monitoring and control of learning strategies, and reaction and reflection phases. As learners go through theses phases, self-regulation can occur in the areas of cognition, motivation, behavior, and context. By crossing phases with areas of self-regulation, Pintrich's taxonomy allows for better structure and organization research on SRL.

Relationship of learner and task characteristics with students' SRL in CBLEs.

The following sub-sections summarize key research findings, which showed that both learner and task characteristics play an important role when students engaged in computer-based learning activities (Winters et al., 2008).

Learner characteristics.

Green and Azevedo (2007) found that middle school students who showed a qualitatively larger shift of their conceptual understanding between pre- and post-tests used more advanced strategies (coordinating informational resources, making inferences, stating a feeling of knowing) than students who showed a lower shift. In addition, Green, Moos, Azevedo, and Winters (2008) looked at learner characteristics and found that gifted students learned more in a hypermedia learning task than their non-gifted counterparts. Although there were no significant differences among gifted and non-gifted students on measures of planning, monitoring and interest; gifted students used effective summarization and inferring strategies more frequently.

Learner characteristics such as prior knowledge, self-efficacy (during forethought phase) and monitoring (during performance phase) during learning play an important role during SRL (Zimmerman, 2001). Moos and Azevedo (2009a) used a multi-method to investigate how monitoring during hypermedia learning mediates the relationship of 68 undergraduate students' self-efficacy beliefs and actual learning outcomes. The researchers (1) measured students' self-efficacy beliefs using a modified version of the Motivated for Strategies Learning Questionnaire (MSLQ; Pintrich, Smith, Garcia, & McKeachie, 1991); (2) used a pre-test and post-test to determine students prior domain knowledge and learning outcomes, respectively; and (3) employed a think-aloud protocol analysis to detect students monitoring processes. The authors found a positive relationship between students' self-efficacy and specific monitoring processes; such as monitoring understanding, monitoring environment, and monitoring progress toward goal. In addition, the study showed that prior domain knowledge did influence students' monitoring of understanding. And lastly, self-efficacy was predictive of students' learning outcomes, when controlling for students' monitoring for understanding and environment.

Nesbit and colleagues (2006) investigated how 80 undergraduate students' achievement goal orientation is related to students' learning tactics. The researchers collected trace data (time stamped data traces of students' learning activities) using the gStudy software, as well as self-report measures to determine students' achievement goal orientation (mastery approach, performance approach, or performance avoidance). The researchers found that students following a mastery approach goal orientation were less likely to use surface study tactics and used more words in "elaborative notes" during the learning task.

Task characteristics.

Whereas Nesbit et al. (2006) looked at students' existing achievement goal orientation, Moos and Azevedo (2006) randomly assigned 60 undergraduate students to one of three learning goals conditions (mastery, performance-approach, or performance-avoidance) in two hypermedia learning task. Their manipulation of students' goal structure did not reveal any differences on motivational (MSQL; Pintrich, 1991) and learning measures; as well as monitoring, strategy use or management of task difficulty. Students in the performance-avoidance goal orientation group, however, showed more planning through (1) recycling goals in working memory and (2) activation of prior knowledge compared to students in the other two conditions.

An earlier study by Schunk and Ertmer (1999) also investigated the influence of students' goal orientation and self-evaluation in an undergraduate "Introductory to Computers in Education" course. Whereas a process goal orientation was associated with learning, a product goal orientation was associated with performance. The researchers assigned 44 students to one of four conditions, namely (1) process with self-evaluation,

(2) process without self-evaluation, (3) product goal with self-evaluation and, (4) product goal without self-evaluation. Similar to Moos and Azevedo (2006), the outcome measures did not reveal any significant group differences, however, process goals were found to be positively related to self-efficacy scores, self-judged learning progress, self-regulatory competence, and strategy use. In addition, continued self-evaluation influenced students' self-efficacy.

Winters et al. (2008) analysis also looked at studies that dealt with learner control in CBLEs. Research (Young, 1996; Eom and Reiser, 2000; as cited in Winters et al., 2008) shows that middle school students who are low self-regulators performed better in a program controlled computer environment than in a student controlled environment. In addition, students classified as high-self-regulators outperformed low-self-regulators in a learner control condition.

Learning supports and conditions, and the quality of students' SRL in CBLEs.

Winters et al. (2008) further looked at research related to the role CBLEs play in enhancing the quality of students' SRL. The authors organized literature in their analysis, following Hannafin, Land, and Oliver's (1999) classification of open learning environments as (1) support tools, (2) conceptual supports, and (3) metacognitive supports.

Support tools.

Support tools are part of CBLEs and help learners to manipulate the content (resources and ideas). Typical support tools allow learners to create content, take notes, or highlight information. Based on Zimmerman's (2001) model of SRL, Kitsantas and

Dabbagh (2004) looked at whether different Web-based pedagogical tools (WBPT) supported different self-regulatory processes. An online survey of 80 college students revealed significant differences among four categories of WBPTs: (1) administrative tools supported self-monitoring and help seeking; (2) collaboration and communication tools were rated more influential on students' goal setting, help seeking, and time planning and management; (3) content creation and delivery tools aided students during self-evaluation, setting of task strategies, and goal setting; and (4) hypermedia tools were most useful in supporting task strategies. These findings were confirmed in a follow-up study (Dabbagh & Kitsantas, 2005) employing a mixed methods design with 65 students distributed across three courses. In addition, qualitative data revealed that WBPTs were supportive in activating key self-regulatory processes during learning tasks and completion of course assignments.

Using a trace data approach, Proske, Narciss, & Korndle (2007) used a web-based learning environment, called "Studierplatz," to investigate whether actual use of the tool increased the interactivity with the system. While the results were generally not supportive of increased use, students who did interactively engage with the system (use of notetaking and monitoring tools) showed higher achievement scores than the other students. The authors conducted a similar study (Narciss, Proske, & Korndle, 2007) as part of TU Dresden's Study2000 project. This study investigated students' engagement with an authoring tool, which was developed to promote active learning and metacognitive activities in an online learning environment. The results showed that whereas most of the time (70%) was used studying texts, hardly any time was spent on using metacognitive support tools. Time spent on learning tasks (11%) and active learning tools (12%) was also limited.

Conceptual scaffolds.

Moos and Azevedo (2008) investigated the impact of conceptual support scaffolds on self-efficacy, monitoring, and planning while learning in a hypermedia learning environment. The researchers assigned 37 undergraduate students to either a conceptual scaffolding or a control condition. Analysis of think-aloud protocols revealed that students who received a conceptual scaffold engaged in more planning activities compared to students who did not receive conceptual support. This study further showed a decrease of SRL activities, especially self-efficacy, over time.

Azevedo, Moos, Greene, Winters, and Cromley (2008) compared how SRL and externally-facilitated SRL (ERL, external scaffolding) impact on students' learning during a hypermedia learning task. One hundred twenty-eight middle-school and high school students were randomly assigned to either a SRL or ERL condition. The researchers found that students in the externally-regulated condition had significantly more gains in their declarative knowledge than their SRL counterparts. In addition, data from think-aloud protocols revealed that ERL students more frequently activated prior knowledge, engaged in more monitoring activities, utilized more effective strategies, and engaged in adaptive help-seeking. Post-test results also revealed that ERL students demonstrated more advanced mental models.

Manlove, Lazonder, and Jong (2007) looked at software scaffolds during scientific inquiry. Twenty dyads received a full version of a Process Coordinator (PC+), which was designed to help students' efforts to plan, monitor, and evaluate their inquiry.

Fifteen dyads, who received an “empty” PC shell without additional scaffolded support (PC-), served as a control group. Students in the PC+ condition used the PC more frequently and for longer amounts of time; also, setting more goals and producing better lab reports. PC- students, on the other hand, set fewer goals and accessed help files more frequently. Contrary to the researchers’ expected study outcome, PC- students produced better content models than students in the PC+ group. The authors attribute this outcome to two possible factors; namely, (1) differential time use left less time for students in the PC+ condition, and (2) more frequent access of help files in the CP- condition directly translated to a higher model quality.

Metacognitive support tools.

The potential of CBLEs as metacognitive support tools have been explored by many researchers (e.g., Kaufmann, 2004; Azevedo, 2006; Graesser et al., 2007; Hadwin et al., 2007, Rouet & Bigot, 2007; Kaufman, Ge, Xie & Chen, 2008), however the results do not give a clear and conclusive picture. For instance, Kauffman (2004) conducted a study with 119 undergraduate students who were randomly assigned to one of eight cells in a 2 x 2 x 2 factorial design: Students in the (1) cognitive strategy used note-taking methods, students in the (2) metacognitive processing group received self-monitoring prompts, and (3) students in the motivational beliefs group received self-efficacy building feedback. The results showed that whereas self-monitoring prompts were not linked to students’ self-reported metacognitive awareness, students in that group outperformed students in the control group on the outcome measure. In a later study, Kauffman and colleagues (2008) studied metacognition by looking at how problem-solving and self-reflection prompts influenced students’ learning in a complex web-based learning task.

The researchers found that students who received metacognitive prompts wrote with more clarity compared to the students in the control group. In addition, self-reflection prompts positively influenced problem solving skills, when students received problem solving prompts. The authors attribute this to the fact that students only value the purpose of self-reflection when they actually have a better understanding of the actual problem.

Rouet and Bigot (2007) investigated the effects of academic training on metatextual abilities by comparing nine post-graduate students with ten psychology undergraduate students during a learning task in a hypertext environment. The results showed that students with more academic training (experts) outperformed their novice counterparts on a metatextual knowledge test. Students further attended to more relevant sections of the hypertext environment and subsequently wrote better essays.

Graesser et al. (2007) conducted two experiments using a web tutor (a metacognitive tool called SEEK Tutor - Source, Evidence, Explanation, and Knowledge), which provided (1) spoken hints on a mock Google search page, (2) online ratings to determine the reliability of webpages, as well as (3) a note-taking facility to prompt students to reflect about the quality of websites. The results showed that the SEEK Tutor had little or no effect on the various dependent measures and did not improve students' ability to discriminate between reliable and non-reliable information. The researchers attribute these sobering results to a need for better training and metacognitive scaffolding approaches in order to better support Web learning.

Research on self-efficacy and learning in CBLEs.

In a recent article in the Review of Educational Research, Moos and Azevedo (2009b) reviewed literature related to self-efficacy in CBLEs. The authors included a total of 33 studies (experimental and non-experimental), which were primarily based on Bandura's (1986) definition and conceptualization of self-efficacy. The authors looked at variables that were related to (1) how students learned in and through CBLEs, as well as (2) what students actually learned. Their findings (in non-experimental research) showed that computer self-efficacy is influenced by both behavioral (e.g., prior usage and corresponding mastery experiences) and psychological factors (e.g., positive attitude, intrinsic interest, curiosity about CBLEs). Experimental research has shown that behavioral modeling showed a stronger impact on learners' computer self-efficacy than traditional instruction-based training. In addition, a combination of feedback and strategy instruction helped to increase learners' self-efficacy.

The authors noticed that there is a limited body of research that systematically outlines specific factors that influence students' development of computer self-efficacy. In particular, mastery experiences, vicarious experiences, social persuasion, and physiological states (as outlined by Bandura, 1986) may prove as a useful framework for future research. In addition, Moos and Azevedo (2009b) see a need to look at how different CBLEs influence learners' self-efficacy beliefs and propose to distinguish between the computer as (1) a mindtool, in which the computer plays the role as a support tool that may facilitate critical thinking, and (2) a productivity tool, to improve learners' efficiency during a task.

There is relatively little evidence about the relationship between computer self-efficacy and learning outcomes in CBLEs (Moos & Azevedo, 2009b). While some research studies (e.g., Thompson, Meriac & Cope, 2002) suggest that self-efficacy is positively related to learning outcomes, other research (e.g. Mitchell, Hopper, & Daniels, 1994), suggests that this relationship changes with the acquisition of knowledge. For instance, Thompson et al. (2002) looked at the effects that goal setting plays on (n = 90) undergraduate students' Internet self-efficacy during a series of online searches using the Netscape Internet browser. The students had 60 minutes to find names of industrial-organizational psychologists on the Internet and list each psychologist's name and college affiliation. Whereas students in the experimental group had a target of finding at least 70 names, students in the control group were asked to do their best. The findings showed evidence that students in the goal condition produced more results than students in the control group. In addition, there was a positive relationship between correct search results and Internet self-efficacy.

Mitchell and colleagues (1994) analyzed 110 undergraduate students performance on a series of 7 trials of complex computer tasks in a CBLE that simulated the job of an air traffic controller. The results showed that computer self-efficacy in Trial 1 was more highly correlated with performance ($r = .27$) than with students' goals ($r = .09$). Trial 7, however, showed a higher correlation of students' self-efficacy with goals ($r = .85$), compared to performance ($r = .58$). These findings may be indicative that self-efficacy changes with experience and knowledge acquisition. Future research and corresponding methodological approaches should account for changes in computer self-efficacy during learning by measuring self-efficacy at multiple points during learning (Moos & Azevedo, 2009b). Following Bandura's (1997) conceptualization that self-efficacy can vary based on level, strength and generality, Moos and Azevedo (2009b) further recommend that future research also needs to be directed towards measuring learners perception about performing a task with regards to task difficulty, strength and whether self-efficacy can be generalized to similar activities.

Current research has looked at the relationship of computer self-efficacy and students' use of certain components of CBLEs; however, more research is needed to investigate the relationship to other psychological factors during learning tasks in CBLEs. For instance, while Lajoie and Azevedo (2006) have shown that SRL processes facilitate learning in CBLEs, Azevedo, Guthrie, and Seibert's (2004) study found that some students do not use key self-regulatory processes at all. Moos and Azevedo (2009b) point out that there is virtually no research addressing the issue of why students are not self-regulating and propose that the concept of computer self-efficacy may be useful in answering that question. In addition, research needs to go beyond focusing on strength and direction of computer self-efficacy, by finding better methods to investigate issues of causality of self-efficacy and processes related to learning in and with CBLEs.

Methodological Approaches Measuring Self-regulated Learning within CBLEs

The following section is based on Zimmerman's (2008) overview of methodological innovations in measuring SRL by highlighting research related to self-regulation in CBLEs. The chapter focuses on research using think-alouds protocol measures (Green & Azevedo, 2007; Azevedo et al., 2007), trace-logs (Winne et al., 2006), and microanalytic measures (Cleary & Zimmerman, 2001; Kitsantas & Zimmerman, 2002).

Think-aloud protocol measures.

Azevedo and colleagues (Azevedo & Cromley, 2004; Azevedo et al., 2007) analyzed students self-regulation in a hypermedia environment (Microsoft Encarta) using a sophisticated think-aloud procedure, where students elaborate on their activities while engaging in a learning task about the circulatory system. The circulatory chapter of Microsoft Encarta is comprised of 16,900 words, 18 sections, 107 hyperlinks and 35 illustrations.

In their earlier work, Azevedo and Cromley (2004) looked at the impact of training sessions based on key self-regulatory processes to foster conceptual understanding and found that college students who received training showed a shift in mental models. Think-aloud procedures during students' inquiry task showed that the shift was associated with the SRL variables taught during training. Green and Azevedo (2006) validated these findings by looking at adolescents' use of self-regulatory learning processes in hypermedia environments. Shifts in mental models have been observed in metacognitive monitoring activities, learning strategies, and indications of task difficulty. Azevedo, Cromley, Winters, Moos, and Greene (2006) see their line of research as a valuable contribution to highlight "the complexity of self- and externally-regulated processes and the corresponding hierarchy of feedback loops during learning in laboratory studies and in learner centered science classrooms" (p. 102).

Azevedo et al. (2008) also used think-alouds to examine differences between self- and externally-facilitated scaffolds and found that students in the externally regulated group outperformed the comparison group on both measures of declarative knowledge as well as mental models.

Zimmerman (2008b) sees advantages of this approach in that it is open-ended, and that coding can be done at a later point by experienced and trained observers. Coding agreement of the verbal protocols into 35 SRL categories (which can be grouped into planning, monitoring, strategy use, task difficulty and demands, and motivation) has been generally high; however, it is very labor intensive. For instance, Greene and Azevedo (2007) coded and analyzed 17,256 verbal segments with an interrater agreement of $\alpha = .97$. Results of this study showed that only six SRL categories significantly predicted middle and high school students' mental models about the circulatory system in the areas of (1) difficulty and demand (control of context), (2) strategy use (coordinating information resources, inferences, knowledge elaboration, and expectation of adequacy of information) and (3) monitoring (feelings of knowing). Planning and motivation did not yield any significant predictors.

Trace logs.

Winne (2006) discussed the role of software technologies and their importance for successful implementation. Since evaluations range widely, the question is still open whether and how software technologies can enhance learners' knowledge and contribute to national goals for education. In addition, he points out the limitations of classical experimental research because the presence of an intervention or training "does not generate a logically sufficient basis for an account about how knowledge was constructed" (p. 8). He further suggests that researchers "have to 'get inside' the time period between the independent variable and the dependent variable" (p. 8). Although, Winne acknowledges concurrent think-aloud protocols (Greene & Acevedo, 2007) and free descriptions/self-reports surveys (Dabbagh & Kitsantas, 2005), he points out that think-alouds may induce metacognitive monitoring into ongoing learning activity, that otherwise would not have occurred. In addition, Winne indicates that self-report questions are often too widely phrased and removed from the time when the actual processes took place.

Winne (2006) suggests a trace data approach in order to measure what learners do while operating in CBLEs. Trace data requires a time-stamped record of events, which allow grounded interpretations about how learners construct knowledge. In other words, trace data reveal whether, when, and how learners access information from the system. It is important to note that Winne refers to all accessible information as prior knowledge, combining both cognitive and computer system knowledge. The researchers get a detailed view of the learners' actual engagement in learning and are better able to avoid under- or miss-specification of their models with respect to constructs like metacognitive monitoring, elaborating, searching for information and recall of prior knowledge. In addition, the measurement of variance occurs during the learning task, as opposed to being based on a priori assumptions.

Following the trace data approach, Winne and his colleagues developed gStudy out of the Learning Kit Project (Nancy & Winne, 2006; Winne, 2006). The gStudy software is a shell, which allows learners to study a learning kit about any topic. Its mission is to gather fine-grained time-sequenced data that traces how learners mediate instruction and SRL. These high goals, however, can only be achieved if the development of such software is part of a larger project (Winne & Perry, 2006); and, given the existing technological restrictions, result in a rather narrow view of self-regulation as a complex feature of learning (Nenninger, 2006). Nolen (2006) also sees measurement problems and raises validity concerns since the researchers are not able to determine why the students do what they do, as well as how they actually use strategies to move through the learning kit. Nenninger suggests including socio-cultural concepts (Boekaerts & Corno, 2005, as cited in Nenninger) in independent learning and expanding the view of self-regulation “to a view of how autonomous learners self-direct their own learning based on the current interests and the objectives they want to achieve” (p. 236).

Microanalysis.

Zimmerman developed a microanalytic method (Cleary & Zimmerman, 2001; Kitsantas & Zimmerman, 2002) in order to analyze the three sequential phases of a self-regulatory feedback loop: forethought, performance and self-reflection (Zimmerman, 2000). Microanalyis uses targeted questions at key points before, during and after learning, in order to measure key self-regulatory processes and motivational beliefs (Figure 2). These measures are open- or closed-ended questions and must be adapted to each performance context. For instance, the following question was developed by Zimmerman and Kitsantas (2002) to measure female expert, non-expert and novice volley ball players’ self-efficacy, “On a scale from 0-100 with 10 being Not Sure, 40 being Somewhat Sure, 70 being Pretty Sure, and 100 being Very Sure, how sure are you that you will make two serves in your opponent’s highest designated area?” Zimmerman (2008b) pointed out that a key feature of microanalytic measures is that the brevity allows for repeated use during a particular task, which may lead to an exploration and analysis of trends during performance. It can further be used to investigate learners’ calibration by comparing his or her perceived level of competence with his or her actual performance.

Microanalysis, to date, has been used to investigate SRL key-processes during the learning of an athletic skill and revealed significant differences between experts and novices (Cleary & Zimmerman, 2001; Kitsantas & Zimmerman, 2002). Although, the acquisition of a self-regulatory skill may take years (Ericson, 2006; as cited in Zimmerman, 2008b), Zimmerman (2008b) indicated that the teaching of "multiphase SRL strategies" (p. 179) significantly improved both athletic skill and motivational beliefs (Cleary, Zimmerman, & Keating, 2006).

Issues of students' calibration in CBLEs.

Students' abilities to judge how well they can perform a particular task (calibration of self-efficacy), as well as how well they actually performed on a specific task (calibration of self-evaluation) have increasingly gained attention by researchers in the field of SRL (for detailed review of literature see Stone, 2000; Chen & Zimmerman, 2007) and metacognition (for detailed review of literature see Pieschl, 2009, Bembenutty, 2009). However, there are only a select few of studies addressing issues of calibration in CBLEs. Most notably, Winne and Jamieson-Noel (2002) looked at how well 69 undergraduate students were able to calibrate self-reports, and their study tactics and achievement using the PrepMate tool, which is part of the Study (later called gStudy; Winne et al., 2006) software. Their analysis was based on Winne and Hadwin's (1998) model of self-regulated studying where students engage in an evaluation process by comparing products (information that is newly created and manipulated through cognitive processes) with a cognitive standard (ideal standard that a product can have). If standard and product profiles do not overlap, the learner cognitively adapts learning strategies until these standards are met. The results of Winne and Jamieson-Noel's (2002) study showed that students were positively biased (overconfident) about both their achievement and actual use of study tactics. Students' calibration on outcome measures, however, was significantly lower than calibration on self-regulatory processes (such as study tactics).

Males generally showed more overconfidence than females. Additional regression analyses revealed a negative relationship for calibration of achievement; which can be interpreted as a decrease in students' test scores as their calibration improves. These findings were substantiated by the same research group in a later case study with eight undergraduate students (Hadwin, Nesbit, Jamieson-Noel, Code, & Winne, 2007). The case study results showed eight different SRL profiles which led the researchers to challenge past approaches to measuring SRL. In particular, they argue for a more fine-grained trace data analysis of students' studying events in CBLEs, and caution the interpretation and use of self-report data due to students' poor calibration. In their view, logs of trace data allow for an accurate assessment of the discrepancies of what students believe they do in CBLEs and what they actually do.

While the concept of calibration (as the discrepancy about one's beliefs about performance and actual performance) seems intuitive; measurement of calibration poses a series of challenges (Brannick, Miles, & Kisamore, 2005). Schraw (1995) highlights the importance of reliably measuring "feeling of knowing" judgments by employing multiple calibration measures. He sees this as an important step toward gaining a better understanding of metacognition and SRL processes. Pajares (1996) and Pajares and Graham (1999) followed this recommendation by looking at students' calibration during math achievement. The researchers employed both mean bias and mean accuracy scores. Mean bias scores show the direction of the error by subtracting actual performance (e.g., where a value of 8 corresponds to a correct answer and 1 to an incorrect answer) from predicted performance (e.g., by using a self-efficacy scale ranging from 1 to 8, where 1 indicates low self-efficacy and 8 high self-efficacy). Consequently, mean bias scores in the present example (Pajares & Graham, 1999) can range from -7 to +7. The mean accuracy score reveals the magnitude of the error and can be calculated by subtracting the absolute value of each bias score from the difference in values assigned to a correct answer and an incorrect answer (in our example 8 – 1 = 7). By looking at our example above, a score of 0 would indicate complete inaccuracy and a score of 7 would correspond to complete accuracy.

Methodological challenges and future research on SRL in CBLEs.

In a recent article on emerging issues in research on SRL, Zimmerman (2008b) addressed a series of implications and topics for future research. This section will highlight his main points and draw comparisons to Winters et al. (2008) recommendations, which should guide future investigations on students' SRL in CBLEs.

Zimmerman (2008b) identified a strong need for more research on issues related to students' accurate judgments of using key self-regulatory processes. While research (e.g., Winne & Jamieson-Noel, 2002) found evidence about students' poor calibration in CBLEs, research in non-CBLEs (Stone, 2000) also showed that there is a positive relationship between students' self-regulatory processes and their calibration. However the causation of that relationship has yet to be determined. Zimmerman (2008b) points out that research related to issues of calibration is essential to investigating students' accuracy during self-monitoring.

Issues of measurement will have to be addressed by comparing different approaches for measuring key self-regulatory processes. Winters et al. (2008) advocate for combining trace data approaches with self-report measures (e.g., think-alouds). By combining multiple approaches, researchers will be able to measure SRL in a more holistic way by measuring behavioral, cognitive and motivational processes. Zimmerman (2008b) points out that microanalytic measures will especially help to determine what motivational feelings and beliefs influence and sustain students' SRL, since the researchers will be able to ask targeted questions at specific points during the recursive SRL cycle (e.g., Zimmerman, 2002). Utilizing these measures has a potential to advance research on the role of self-efficacy during various phases of learning, which was suggested as a future research area by Moos and Azevedo (2009a).

Winters et al. (2008) further point out that research has yet to address the quality of the SRL processes and that future studies should pay more attention to how SRL is linked to learning outcomes. Particularly, the latter is important in order to determine which CBLEs foster students' SRL and translate to better learning outcomes. For instance, research has yet to explain why certain group differences in key self-regulatory processes exist without corresponding differences in learning outcomes (e.g., Azevedo, 2006; Graesser et al., 2007).

Many studies on SRL in CBLEs use support tools (e.g., embedded or external prompts, feedback or scaffolding) to foster students' acquisition of self-regulatory skills (e.g., Kitsantas & Dabbagh, 2004; Dabbagh & Kitsantas, 2005; Proske et al., 2007). Winters et al. (2008) argue that these tools need to be removed at some point during the investigation of SRL acquisition, in order to be able to truly talk about the acquisition of self-regulatory skills. Within the context of CBLEs, Zimmerman and Tsikalas (2005) suggest following Zimmerman's (2000) social multilevel model of self-regulatory development.

Self-regulated Learning and Internet Searching

There is fairly little empirical support about students' self-regulation during Internet searching. For instance, Rogers and Swan (2004) asked 80 undergraduate students at a public university to select one out of eight Internet search tasks and search the Internet in order to answer the selected question. During a 30 minute search task, students' behaviors (total of 8,000) were observed and coded into 39 observable behaviors, which were then categorized into five self-regulation strategies (based on Corno & Mandinach, 1983; as cited in Rogers & Swan, 2004): alert, select, connect, plan, and monitor. Subsequently, these strategies were standardized by calculating (1) standard-use-per-unit time and (2) process-use-per-unit time. Results showed that selecting was the most frequently observed strategy, followed by connecting, monitoring, and planning. Correlations between these observational data did not yield any significant correlations; however, when controlling for contextual features, monitoring was most often linked with selecting.

Guinee, Eagleton, and Hall (2003) investigated the Internet search strategies of 161 middle and high school students using a variety of public domain Internet search engines in Phase 1, such as Google, Yahoo, and AskJeeves (n = 29, M_{age} = 13 years, 4.8 months, SD_{age} = 23.9 months); as well as a Web-based software prototype in Phase 2, called eTrekker (n = 132, M_{age} = 13 years, 9.2 months, SD_{age} = 4.9 months), which was developed by the Center for Applied Special Technology (CAST), to scaffold students' Internet inquiries during planning, searching and organizing. Whereas students in both phases had to complete a series of Internet searches, students in phase 2 also had to conduct one of two researcher-designed scavenger hunts. In addition, students in both phases had to complete an Internet-based research project. The constant comparative method was used to identify potential categories, and descriptive statistics were calculated from the trail data in the scavenger hunt in phase 2, which was coded independently by 2 raters (Cohen's *kappa* = .87).

Results showed that students tried to access information by using the "dot-com formula" (p. 367), where the topic of interest was searched by entering an Internet domain such as www.mytopic.com. A second approach used was the "shopping mall" approach, where students went to known internet sites (e.g., www.expedia.com) that they associated with a particular category (e.g., "tours"), and subsequently searched these websites for information. As students gained more familiarity with some of these websites, they increasingly used this approach. The third and last approach that Guinee et al. (2003) identified was the use of search engines and the construction of related search strings. The following part will summarize (1) search strings that students constructed, and (2) approaches for recovery in case of unsuccessful searches.

Search string methods.

Guinee et al. (2003) identified a total of seven different methods that students used in order to construct search terms: single term, topic + focus, multiple terms, phrase, question, combination, and repeated concept:

The *single term* method, which is the most basic form, is used when students enter only the word that they are looking for (e.g. "James Bond"). During the scavenger hunt questions, this method was used by 64.5% of the students with a mean of 43.7% (*SD* = 25.5) searches.

The *topic + focus* method is employed when entering both a topic (e.g. “James Bond”) as well as a focus (e.g. “actors”) into the search engine. This method was used by 66.7% of the eighth graders during an average of 37.0% (*SD* = 25.4) of the searches. Guinee et al. (2003) highlighted the effectiveness of this approach since the percentage of its use was significantly negatively correlated with a number of search attempts ($r = -.23$, $p < .05$). The *multiple terms* method is an extension of the *topic + focus* method by adding additional foci to the search string (e.g. “James Bond + actors + played”). This method was used by only 19.4% of the students with a mean of 27.7% (*SD* = 20.3) of searches completed.

More than half (51.6%) of the students entered entire *phrases* (e.g. “president got stuck in the bathtub”), which was considerably less effected as shown by a significant positive correlation with number of search attempts ($r = .22$, $p < .05$). Students (29%) also entered entire *questions* (e.g. “How many actors played James Bond?”) for an average of 31.8% (*SD* = 20.9) of their searches; or *combinations* (6.5% of the students) by combining a discrete term (e.g. “James Bond”) with phrase fragments (e.g. “number of actors) with a mean of 19.9% (*SD* = 17.9) of their searches. And lastly, 29% of the students entered *repeated concepts* in their search terms (e.g. “actors that played James Bond + James Bond actors”) with an average of 32.8% (*SD* = 21.2) of searches made. This method was considered the least efficient since its use showed a significant positive correlation with search attempts made ($r = .35$, $p < .001$).

Responses to unsuccessful searches.

Guinee et al. (2003) also found evidence of 4 distinct techniques that students used in the case of unsuccessful searches. Similar search patterns (7) have also been observed in Rogers and Swan (2004) among college students.

Guinee et al. (2003) showed that when students were given the ability to research a topic of their choice, they often desired to *switch topics* if they had not been able to find the desired information online. This approach is reactive in its nature, since it is not planned and follows an original search attempt. Depending on the situation, this approach can be considered adaptive or dysfunctional.

Students also selected *additional websites* from the results page, if the top results did not yield satisfactory information. This strategy is highly dependent on how carefully the search terms are chosen, since qualitatively higher search terms lead to better search results. Important here is students' ability to determine the relevancy of the search results before choosing a web site for further investigation. A similar pattern was found by Rogers and Swan (2004) where students used visual cues to determine a site's content relevancy before selecting a site from a list of links.

The third response to an unsuccessful search event is to *try new keywords*. This can be done by using synonyms to the original keyword, by narrowing or broadening the focus, or by checking the spelling of the keyword. Rogers and Swan (2004) found that college students refine and select new keywords in a successive and progressive manner. And lastly, students may chose to *select a different search engine* if the search results are not satisfactory. They may even split their browser windows in order to better compare the search results (Rogers & Swan, 2004).

The Online information searching strategy inventory (OISSI).

While there has been very limited empirical evidence on online searching, self-regulation and corresponding strategies, a recent investigation by Tsai (2009) developed a self-report instrument to evaluate student online information searching strategies. The Online information searching strategy inventory (OISSI) has both a short and a complete version. The 13 item short version, which is loaded onto three factors (metacognitive, behavioral, and procedural), had a total reliability $\alpha = 0.85$. The longer version (reliability $\alpha = 0.91$) is comprised of 25 items and is loaded onto seven factors (disorientation, evaluation, purposeful thinking, trial and error, select main ideas, control, and problem solving). Scores on 324 Taiwanese high school students revealed gender differences in behavioral and procedural domain strategies, however no differences were found in the metacognitive domain. Additionally, while behavioral domain strategies were found to be significantly related to online search hours, procedural and metacognitive domain strategies were not. These results may be indicative of the fact that an increase in the amount of searches is not necessarily related to the use of higher forms of search strategies, exemplifying students' metacognitive challenges during online inquiry (Quintana et al., 2005).

While these results shed some new light on students' online searching strategies, Tsai (2009) acknowledges the limitations of a self-report measure and recommends further examinations of these findings by looking at log files, which are similar to Winne's (2006) trace data approach. In addition, motivational aspects and learning outcomes need to be considered in future research, as well as strategy scaffolding approaches in order to help students to better develop metacognitive domain strategies for successful online searching and meaningful online learning and inquiry.

The Role of Feedback to Overcome Metacognitive Challenges in CBLEs

According to Hattie and Timperley (2007) feedback is the “consequence of performance” (p. 81), it is content dependent and it never occurs in a vacuum. Research has shown that while some feedback is effective in reducing the discrepancy between current understandings and goals, some are not. Hence, it must be guaranteed that feedback is targeted at an appropriate level (Hattie & Timperley, 2007). Unfortunately, this is not always simple to achieve. In CBLEs, students are required to construct knowledge with the help of computers and rely most of the time on the feedback that is provided through the computer, however, this kind of feedback may not always have power to initiate further action (Proske et al., 2007; Azevedo et al., 2008). In addition, feedback may also be sought by the learner and hence, be detected without being intentionally sought (Hattie & Timperley, 2007). This type of feedback is internal in nature and relies on the monitoring process when learners are evaluating their performance (Lajoie, 2008).

Given the complexity of online inquiry tasks, and the ambiguity of how students receive/seek and interpret feedback, students face certain metacognitive challenges. Research (Quintana et al., 2005) has shown that students need to be provided with an appropriate scaffolding to overcome metacognitive challenges during inquiry activities. To overcome these challenges, Quintana et al. proposed a framework for supporting metacognitive aspects through the use of software-based scaffolding by comparing cognitive sub-processes of novices and experts in an online inquiry during the following phases: (1) asking questions, (2) searching, (3) evaluating and reading, and (4) synthesizing. During each of these four cognitive processes the learners engage in a sequence of metacognitive activities, namely, (1) task understanding and planning before the task, (2) monitoring and regulation during the task, and (3) reflection after the task.

Quintana et al.'s (2005) framework mentions the following metacognitive challenges that the students face during online inquiry. During (1) *task understanding* the learners often ask simple questions that sometimes only require factual information. By looking for a "magic" website, they have further difficulties planning the tasks. In addition, they often quickly skim through the material without a clear purpose. Challenges related to (2) *monitoring and regulation* could be the premature abandonment of questions if students fail to find the appropriate information. This coincides with a lack of being able to identify the appropriate search queries, as well as being easily distracted when reading webpages. The learners often have difficulties in establishing qualitatively high criteria during the synthesis of their findings. The challenges have further been substantiated in a recent study by Moos and Azevedo (2008), who found that learners in a hypermedia environment decreased their monitoring processes as they moved through the learning task. During the (3) *reflection* phase students fail to reflect on the content and the quality of their inquiry questions, on the actual search process, on the reading strategies and evaluation criteria used, and, last but not least, they rarely reflect on how they concluded their argument. Unrelated to Quintana et al.'s framework, Lim (2004) developed similar guidelines in his study about design issues of inquiry-based learning environments.

Missing in Quintana et al.'s (2005) framework is the role of motivation and one's own beliefs. These processes have been discussed within the context of self-regulation in CBLEs (Azevedo, 2005; Azevedo & Cromley, 2004; Azevedo et al., 2006; Graesser et al., 2005; Kauffman, 2004; Zimmerman & Tsikalas, 2005), computer-supported collaborative learning environments (Dabbagh & Kitsantas, 2004, Kitsantas & Dabbagh, 2005; Salovaara, 2005), or the use of the Internet as an epistemological tool for instruction (Tsai, 2004).

White and Frederiksen (2005) believe that the theory of scientific inquiry can become a general theory of learning through inquiry, meaning, that "[m]anaging and improving one's inquiry processes depends on students' having full knowledge of the cognitive, social, and metacognitive capabilities that are needed for learning via inquiry" (p. 214). Their theory, which is based on cognitive modeling, was expanded to also include pedagogical activities (ranging from guidance software advisors to peer advisers) and sees advisors interacting collaboratively, while recognizing that each student has a particular expertise within this model. It is through this interaction that students are able to develop their theory of cognitive and metacognitive processes that ultimately lead to transfer to other learning contexts.

A Social-cognitive Multi-level Model of Self-regulatory Development in CBLEs

Zimmerman and Tsikalas (2005) and propose a social-cognitive multilevel model of self-regulatory development because "optimal forms of self-regulatory training are initially social in form but become increasingly self-directed" (p. 270). Learners learn to acquire a new skill through observing proficient models and subsequent training. This learning process requires the learner to master four sequential levels of skill:

(1) Observational level: learners attain skills from a proficient model's performance or description when they are able to discriminate the correct form of the skill. (2) Emulation level: the skill is actually attained when the learners are able to generalize the models' actions to a similar task. (3) Self-controlled level of self-regulatory skill: the learners can practice on their own without the presence of the model. (4) Self-regulated level of task skill: learners learn to adapt their skill based on performance outcomes during practice in personal and contextual conditions. This model has already been tested by looking at how college students use modeling and social feedback on the acquisition of writing revision (Zimmerman & Kitsantas, 2005). Since online inquiry and the synthesis of its findings operate in a similar – namely text-based – environment, it may be used as an alternative model to study the role of self-regulation and how proficient (expert) models can help students to overcome metacognitive challenges in CBLEs. In a recent publication on self-regulatory strategy training with integrative learning technologies (ITS), Kitsantas and Dabbagh (2010) illustrate research and practical suggestions on how Zimmerman's (2000) model can be used during self-regulatory skills acquisition in CBLEs. The present training study will follow this framework by modeling an expert online search strategy. I hypothesize that:

(1) There is a positive effect of expert-modeling on students' achievement in an online-based inquiry task.
(2) There is a positive effect of expert-modeling on mediating key self-regulatory processes.

(3) Students in the expert-modeling group are better able to calibrate their judgments of predicted outcomes (self-efficacy, self-evaluation) with actual outcomes than students in the control group.

Corresponding to the hypotheses outlined above, I would also like to answer the following research questions:

(1) What key self-regulatory processes predict achievement during the inquiry tasks?

(2) Is there a qualitative and quantitative difference in the search queries (search terms) entered into Google between the two treatment conditions?

(3) Is there a qualitative and quantitative difference in the websites selected during online inquiry between the two treatment conditions?

CHAPTER THREE

METHODOLOGY AND PROCEDURES

Sampling and Research Participants

Participants for this study were recruited from various sections of Freshmen English (first college-level English course) at a large urban community college in the Northeastern U.S. As an incentive, students were offered monetary compensation in the amount of $30 for their time and effort. Students who signed up for the study were asked, "How do you use the Google search engine for research on the Internet?" and grouped into the following categories: novice (student had little or no experience using the computer or Internet), non-expert (student was familiar with using the computer and Internet but did not indicate any advanced online research skills, e.g. Topic and Focus Strategy or use of search operators), expert (student was familiar with using the computer and Internet and indicated advance online research skills, e.g. Topic and Focus Strategy or use of search operators). In their investigation of self-regulated learning in web-based learning environments, Narciss, Proske and Koerndle (2007) pointed out that learners with limited experience in web-based environments may encounter difficulties in translating their usual learning into these, often unfamiliar, learning environments. Consequently, only students with moderate experience (non-experts) were considered for this study, since they were already familiar with the basic functionality of the Google search engine without necessarily employing expert behaviors as outlined in Quintana et al.'s (2005) framework.

According to Cohen (1992), a sample size of N = 26 is suggested in each group for power of .80 in order to detect a large difference between two independent sample means at $\alpha = .05$. Kitsantas & Zimmerman's (2002) microanalytic study on self-regulation yielded highly significant results with a sample size of 10 students. Hence, a sample of 40 students (20 per treatment condition) was used in this study. The sampling unit was students.

The final sample (n = 40) of this study showed that all students were familiar with using the computer and Internet and did not indicate any advanced online research skills, such as Topic and Focus Strategy or use of search operators. The research participants were all considered "non-experts." Further, the sample (28 females and 12 males) was comprised of 32.5% African Americans, 27.5% Caucasians, 27.5% Hispanics, and 12.5% Asians. The average age was 20 years and 3 months ($M_{age} = 20.25$, $SD_{age} = 2.64$). All participating students graduated from a high school in the United States and took the SAT exam. The average SAT reading score of the sample was $M_{SATr} = 455.26$, $SD_{SATr} = 84.69$; and the average SAT math score was $M_{SATm} = 450.26$,
$SD_{SATr} = 81.82$. SAT writings scores were not available for all students.

Online Inquiry and Trace Data Collection Tools

The Google search engine has become the most widely used search engine on the Internet. Students enter search queries into the search field and receive search results (see Figure 3) based on a sophisticated algorithm called PageRank (Google, 2009). Once students enter search terms into the search field, Google automatically suggests related search terms in a drop-down menu.

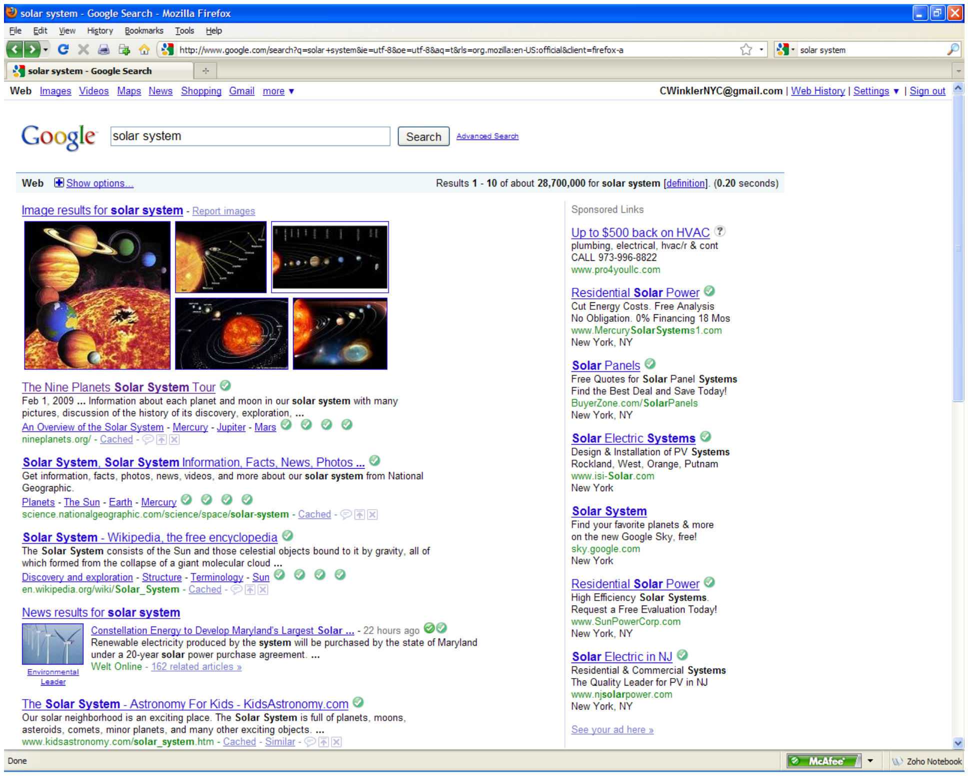


Figure 3. Screenshot of an example of a Google search result

Since this feature (cognitive scaffolding tool) may confound the results of the study, it was turned off during the study (this can be done in the user settings of any Google user account). Google users who sign up for a Google account have access to a multitude of additional online tools. Of particular importance to the proposed study was a detailed time-stamped log, or Web History, of the user's search history including search queries entered and websites selected. In order to trace students' selection of information, the Zoho Notebook was used. This web-based tool allows users to automatically clip (paste) any highlighted information (text, pictures, etc.) into a virtual clipboard (see Figure 4).

Figure 4. Screenshot of web browser using the mini Zoho Notebook function

This can be done from any website or html-document that is displayed in a web-browser using Mozilla Firefox. The Google web history and the Zoho Notebook were used to collect time-stamped trace data.

Expert-Modeling Strategies

Topic-focus strategy.

The expert strategy modeled in this study is based on Eagelton and Dobler's (2007) QUEST model "that engages and supports students as they tackle the complexities of reading on the Web" (p.51). The QUEST model of Internet inquiry is similar to Quintana et al.'s (2005) framework and is comprised of five distinct phases, namely (1) Questioning, (2) Understanding Resources, (3) Evaluating, (4) Synthesizing and (5) Transforming. Of particular interest to this study is phase two of the model, which includes a recursive feedback loop that prompts students to answer the questions "How will I find out?" For instance, when learners are looking for information about the *history of the solar system* online, they often make the mistake of selecting search terms that are either too broad, such as "solar system," or, that are too wordy, such as "What is the history of our solar system?" According to this model, the truth lies somewhere in the middle by selecting a search query such as "solar system + history."

Eagelton and Dobler (2007) developed a "topic-and-focus" strategy that helps students to select the right search terms for their online inquiry by (1) circling the topic of the inquiry question, (2) underlining the focus, or focuses, of the inquiry question, and (3) creating search terms by combining topic and focus. In the example above "solar system" would be the *topic* and "history" would provide the *focus*. In addition to this strategy, Eagelton and Dobler exemplified three applications of how the strategy may be used by the students. The first application refers to literal questions, meaning that all search terms can be found directly in the question. The second application requires the students to substitute a word from the inquiry question with another search term, such as "where' with "location." And lastly, students may encounter inquiry questions that may have more than one focus.

Metacognitive monitoring scaffolding strategy.

Metacognitive monitoring scaffolds that were modeled in this study are based on Eagelton and Dobler's (2007) phase three of their QUEST model, which prompts students to evaluate computer-generated feedback (search engine results page) by answering the question "Is this information accurate and useful?" Eagelton and Dobler suggest several strategies of how students can enter the evaluation process. For the purpose of this study, the following metacognitive monitoring scaffolds was introduced to the learners during specific phases of the inquiry cycle: The learners will be trained to answer two sets of questions in order to determine the truthfulness and usefulness of the websites (on the results page) and information within a website (once a website has been selected): (1) Is the site (or information) trustworthy? Why or why not? (2) Does the site (or information selected) match my inquiry question? Why or why not?

Research Design and Procedures

The proposed experimental study combines microanalytic measures with trace data. Forty students showing a moderate skill level in online-based inquiry (non-experts) have been randomly assigned to one of two treatment conditions (Expert-Modeling and Control). A preliminary analysis of the sample showed no significant differences in groups based on age, gender, race, and SAT reading and math scores.

During the pre-treatment phase, (Appendix G gives a detailed overview about the research design, phase and corresponding measures), students in both groups received a general video introduction (recording of audio and corresponding mouse cursor and screen movements) about the Google search engine and Zoho Notebook (Appendix A). Following the video, students were asked to practice what they have seen in the videos by using the Google search engine and clipping five clippings to their Zoho Notebook (Appendix B).

During the treatment phase, based on Eagleton and Dobler (2007), students in the Expert-Modeling group received additional two video instructions (Expert-Modeling Strategies) by an online inquiry expert (Appendix C). The first video introduced the students to the Topic and Focus Strategy, which showed them how to determine the best search queries in order to answer an inquiry question. Subsequently, the second video introduced the students to the Metacognitive Monitoring Scaffolding Strategy to determine the truthfulness and usefulness of search results and corresponding information on websites from the search results. The videos of the modeled behavior were shown in two sequential increments, followed by a 15 minute guided practice period after each video with some basic guidance by the experimenter. The practice period, which conforms to Zimmerman's (2002) emulation and self-control levels when acquiring a self-regulatory skill, was scaffolded by handouts (Appendix D), which followed Eagelton and Dobler's (2007) URL and Hit List Evaluation Handouts. During the practice period Students in the control group received no treatment.

Finally, students in both conditions received an online inquiry question (Appendix E), which they had to answer using the Google search engine (Figure 5 shows the online inquiry model and corresponding measures). The students were given at total of 60 minutes to complete the online inquiry task; of which 30 minutes was allocated for searching, reading and evaluating, and 30 minutes for synthesizing.

The research question, "How is global warming going to impact on the future of humanity?" was very broadly phrased in order to require students to integrate multiple websites into their answer. After a two minute review period, the students were asked questions about their knowledge about the subject matter, self-efficacy beliefs, perceived intrinsic interest, goal setting and planning, in order to measure students' cognitive, metacognitive and motivational processes during the first phase (asking questions) of their online inquiry.

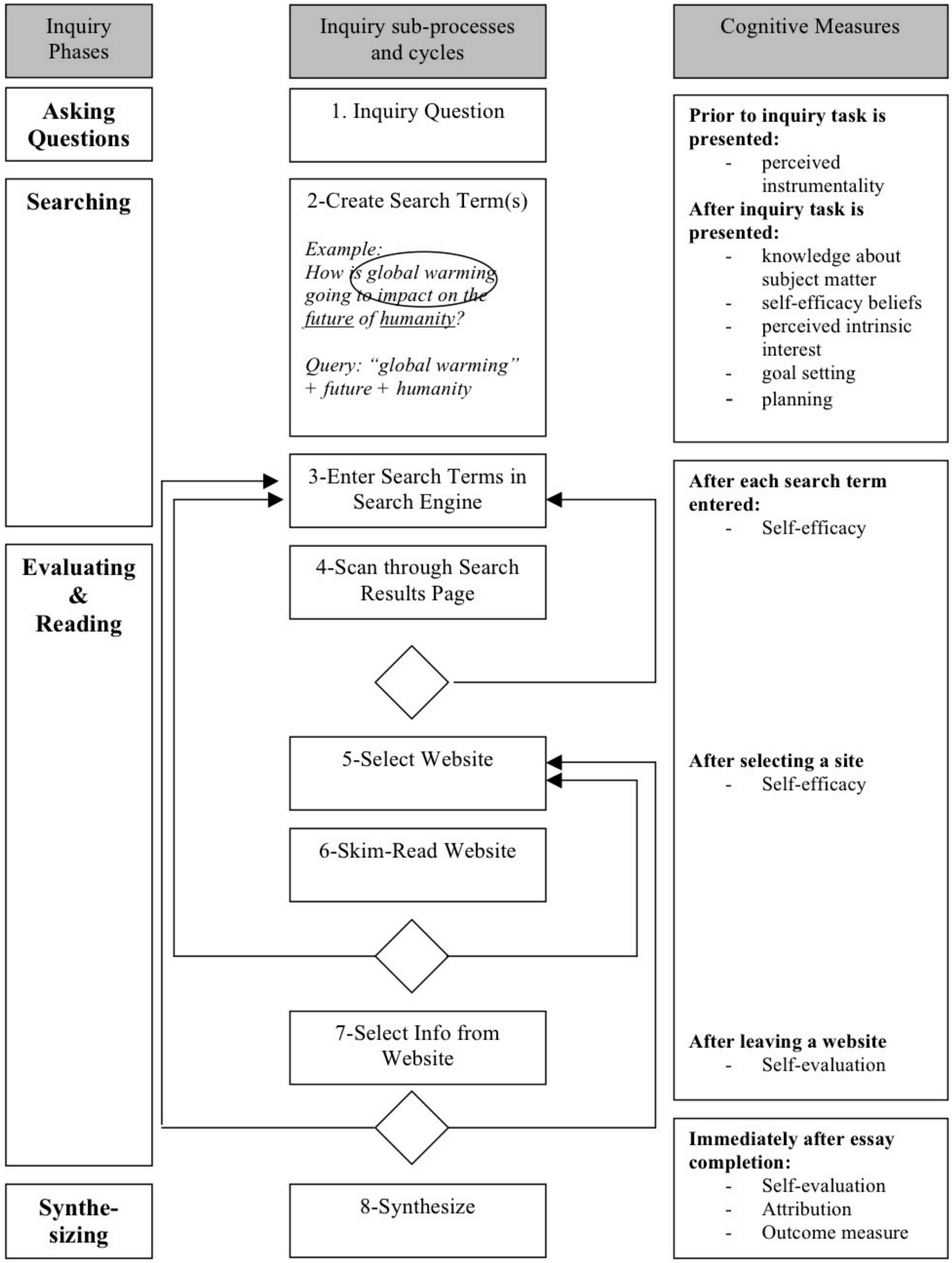


Figure 5. Activities during online inquiry and measures used

During the first part of their online inquiry (phases searching, evaluating and reading), the students were asked to gather information about the research question by using the Google search engine and clipping their research findings from the various webpages to their Zoho Notebook. The maximum time allocated for their search was 30 minutes. This part was characterized by a series of recursive feedback loops, where the students were required to review the Google results page (computer generated feedback) and determine whether they should (1) select a website from the results page for further investigation, or (2) enter a new search term to refine their search terms or to adjust their search strategy. If students selected a website by clicking on the link from the results page, they would subsequently have to skim-read the website and proceed as follows: (1) select information from the website, (2) select another website from the results page, or (3) enter a new search term to refine their search or adjust their search strategy. These processes were repeated until the students were ready to integrate (synthesize) their findings into short written response (approximately 250 words).

During these feedback loops, trace and cognitive data were collected. Google automatically tracked and logged trace data, such as search queries entered, links clicked; and Zoho Notebook tracked the information selected. Cognitive data were collected by asking the students about their self-efficacy beliefs (immediately after entering a new search term and immediately after selecting a site from the results page) and self-evaluation (immediately after leaving a site).

After the students finalized their search, they had 30 minutes to synthesize their findings by writing a 250 words written response from their Zoho Notebook notes. The students were allowed to use their Zoho Notebook notes during this phase and prohibited from conducting any additional research using Google. Prior to writing the written response the students were asked again about their self-efficacy beliefs. And, immediately after completion of the written response, the students were asked to self-evaluate their performance and to answer a question about their attributions.

Measures

Cognitive measures.

Perceived instrumentality. Prior to presenting the inquiry question and in order to assess the students' perceived instrumentality, the participants were asked, "On a scale from 0-100, with 10 being Not Important, 40 being Somewhat Important, 70 being Pretty Important, and 100 being Very Important, how important is using the Google search engine for the attainment of your future goals as an Internet user?"

Prior knowledge about the subject matter. A scale was developed to measure students' beliefs about how much they know about the subject matter. After receiving the novel inquiry question, the students were asked, "On a scale from 0-100, with 10 being Not Able, 40 being Somewhat Able, 70 being Pretty Able, and 100 being Very Able, how able do you believe you would be to answer this question by yourself without using the Google search engine?"

Self-efficacy beliefs. Four self-efficacy scales were used to assess students' confidence about accomplishing their inquiry task using the Google search engine. All four scales are based on Kitsantas and Zimmerman's (2002) and Cleary and Zimmerman's (2001) self-efficacy scales. The first scale was used after the students received the novel inquiry task. The students were asked, "On a scale from 0-100, with 10 being Not Sure, 40 being Somewhat Sure, 70 being Pretty Sure, and 100 being Very

Sure, how sure are you that you will be able to answer the question by using the Google search engine for your research?" The second scale was used to measure the students' self-efficacy after they enter a new inquiry cycle (entering a new search query into Google and pressing the "search" button). The students were asked, "On a scale from 0-100, with 10 being Not Sure, 40 being Somewhat Sure, 70 being Pretty Sure, and 100 being Very Sure, how sure are you that you will be able to answer the question by using the search term you just entered?" The third scale was used to measure the students' self-efficacy after they enter a selected site for evaluation and reading (selecting a website from the search engine results page). The students were asked, "On a scale from 0-100, with 10 being Not Sure, 40 being Somewhat Sure, 70 being Pretty Sure, and 100 being Very Sure, how sure are you that you will be able to answer the question by using the webpage you just selected?" And finally, prior to synthesizing their search results into a written response from their Zoho Notebook, students were asked, "On a scale from 0-100, with 10 being Not Sure, 40 being Somewhat Sure, 70 being Pretty Sure, and 100 being Very Sure, how sure are you that you will be able in answering the question by using the search results you received?".

Perceived intrinsic interest. To assess the students' perceived intrinsic interest, the participants were asked, "On a scale from 0-100, with 10 being Not Interested, 40 being Somewhat Interested, 70 being Pretty Interested, and 100 being Very Interested, how interested are you in using the Google search engine to answer the research question?"

Goal setting. The students were asked if they have set any specific goals for themselves for this task. If the students answered with "yes" they were further asked, "What is your goal for this task?" The answers were recorded verbatim and coded independently by two individuals as follows: "outcome" or "process." For instances, students who responded with "To complete the essay" were coded with "outcome," and students who responded with "Find exactly what the question is asking" were coded with "process." Cohen's kappa procedures were used to determine the inter-rater reliability, *kappa* = 0.88.

Planning. The students were further asked what they needed to do in order to accomplish their goals. The answers were recorded verbatim and coded independently by two individuals as follows: "structured", "somewhat structured", or "unstructured." An example of a structured student response was "Get facts from various websites, use trustworthy info pertaining to questions, and research global warming and different effects." An example of a "somewhat structured" response was "Search Google and check for trustworthy sites," and an "unstructured" student response was "Use Google." Cohen's kappa procedures were used to determine the inter-rater reliability, *kappa* = 0.77.

Self-evaluations. Two self-evaluation scales were used to assess students' perceptions about their accomplishments at specific points during the inquiry tasks using the Google search engine. The first self-evaluation measure was used after leaving a selected website to select a new website from the results page or enter a new search term. Students were asked, "On a scale from 0-100, with 10 being Not Sure, 40 being Somewhat Sure, 70 being Pretty Sure, and 100 being Very Sure, how sure are you that the page you just looked at was helpful in answering the question by using the Google search engine for your research?" Secondly, after completing the 250 words written response, students were asked, “On a scale from 0-100, with 10 being Not Sure, 40 being Somewhat Sure, 70 being Pretty Sure, and 100 being Very Sure, how sure are you that you were be able to answer the question by using the search results you received?”

Attributions. A follow-up question was asked to determine the students' attributions about their performance. All participants were asked, “If your essay was not satisfactory in answering the inquiry question, why do you think this was the case?” Two researchers independently coded the answers into the following categories: personal ability, and task difficulty. For example, students who responded with “Because I used the wrong search terms.” were coded as “personal ability,” and students who responded with “Not enough time” were coded as “task difficulty.” Inter-rater reliability was established using Cohen's kappa procedures, *kappa* = .75.

Behavioral Measures.

Every student received a Google account for the purpose of the study. While being logged into an account, Google automatically logged the entire search history (Figure 3), including the search queries created. The data was used to measure the quantity and quality for: (1) feedback created through entering the search queries, (2) sites visited from the search results, and (3) information selected and clipped to the Zoho Notebook.

To determine the quality of the search queries, each search query entered was coded by two independent raters on a scale from “1” to “5,” where “5” indicated the presence of topic (global warming), and all focuses (future, impact, humanity). A score of “4” was given when the query contained a topic (global warming), the focus “humanity” and one additional focus (future or impact). A score of “3” was given when the search query contained a topic (global warming) and one focus (future, impact or humanity). A score of "2" was given if the search query contained either the topic (global warming) or one focus (future, impact or humanity). And finally, a score of "1" was given if the search term has neither a topic nor focus. In addition, 1 point was deducted in case of wordiness as well as for each additional unrelated focus. Inter-rater reliability was established using Cohen's kappa procedures, *kappa* = .95.

To determine the quality (usefulness to help answer the inquiry question) of the websites selected, a newly developed scoring rubric was used. Two researchers independently coded the selected websites into the following categories: useful, somewhat useful, and not useful.

To determine the quantity of each of the search queries entered, sites visited, and information selected, frequency counts were used.

Outcome measure.

The written responses were scored using a modified version of the SAT scoring rubric (The College Board, 2010; see Appendix F). Since the focus of this experiment was on the synthesis of results in a novel online inquiry task, the essays were not graded on sentence structure, grammar, usage, and mechanics. Similar to the SAT scoring procedure, two independent raters graded the essays on a score from 1-6, with the combined score ranging from 2-12. If the scores differed by 2 points, a third reader was asked to rate the essay. A total of 2 essays needed to be scored by a third rater. A weighted Cohen's kappa (Spitzer, Cohen, Fleiss, & Endicott, 1973) analysis was used to determine the inter-rater reliability (*kappa* = .44). In addition, a Spearman's pairwise correlation showed a significant positive correlation of $r = .75$, $p < .01$.

Calibration measures.

In order to determine students' calibration of self-efficacy, a mean bias score (Pajares, 1996; Pajares & Graham, 1999) was calculated by subtracting the outcome scores (recoded, where a score of 100 corresponds to the initial score of 12) from the self-efficacy scores (after inquiry question is presented and prior to writing the essay). Similarly, a mean bias score for self-evaluation was calculated by subtracting the recoded outcome score from the final self-evaluation score (immediately after completion of the written response).

CHAPTER FOUR

RESULTS

Essay Scores (Hypothesis 1)

It was hypothesized that there is a positive effect of expert modeling of a self-regulatory research strategy and guided practice on students' achievement in an online-based inquiry task. In order to investigate group differences on the outcome measure (short essay), a single factor analysis of variance (ANOVA) was performed. The results showed that group means of the writing scores differed significantly, $F(1, 39) = 4.66$, $p < .05$, $\eta_p^2 = .11$ with the Expert Modeling Strategy group ($M = 7.45$, $SD = .51$) surpassing the Control group ($M = 6.1$, $SD = .37$).

Key Self-regulatory Processes (Hypothesis 2)

The analysis of the second hypothesis of the study dealt with whether the training intervention of the self-regulatory strategy had an effect on any of the nine key self-regulatory measures that were used at specific points during the online inquiry. During the inquiry phase asking question, which corresponds to Zimmerman's (2000) forethought phase, the students were asked about their prior knowledge, perceived instrumentality, intrinsic interest, self-efficacy (when task is presented), goal setting, and planning. In addition, the students were asked about their self-efficacy prior to writing their essay (marking the completion of the phases searching/evaluating), as well as their self-evaluation and causal attribution after completing the essay (marking the end of their synthesis phase). The latter two measures also correspond to Zimmerman's (2000) self-reflection phase. These measures were analyzed in two groups: continuous and categorical variables.

Table 1.

Group Means and Standard Deviations of Metric Key Self-regulatory Measures During Phases Answering Questions, Searching/Evaluating, and Synthesizing

	Control	Expert-Modeling	p-Value	η_p^2
Prior knowledge				
M	50.75	44.50	.35	.02
SD	22.02	21.14		
Perceived instrumentality				
M	83.50	87.75	.37	.02
SD	15.31	13.03		
Intrinsic interest				
M	74.50	80.00	.48	.01
SD	29.46	17.47		
Self-efficacy (after task presented)				
M	85.40	77.50	.77	.00
SD	13.95	10.7		
Self-efficacy (prior writing essay)				
M	79.00	87.50	.10	.07
SD	20.24	10.20		
Self-evaluation (after writing essay)				
M	85.50	86.25	.91	.00
SD	16.38	11.98		

*p < .05

Impact of strategy instruction on continuous key self-regulatory measures.

A single factor multivariate analysis of variance (MANOVA) was used to summarize differences on the six metric key self-regulatory measures during the inquiry phases answering questions and synthesizing: prior knowledge about subject matter, perceived instrumentality, perceived intrinsic interest, self-efficacy beliefs (when task is presented, and right before writing the essay), and self-evaluation (prior to writing the essay). Although the multivariate effect was not significant, $F(1, 39) = 1.22$, $p > .05$, separate univariate *t*-tests indicated marginally significantly higher self-efficacy scores prior to writing the essay in the Expert Modeling group, $F(1, 39) = 2.81$, $p = .10$, $\eta_p^2 = .07$. Means and standard deviations of these measures for both Expert-Modeling Strategy and Control groups can be seen in Table 1.

Since these measures (individually) did not capture the cyclical and dynamic quality of these key-self-regulatory processes, a more detailed examination was needed. Of particular interest to the subsequent analysis was an investigation of how students' judgment about their ability to answer the inquiry questions changed at specific points during their online inline inquiry. Whereas self-efficacy (when inquiry task was presented) marks the beginning of the phase searching/evaluating, self-efficacy (prior to writing the essay) separates phases searching/evaluating and synthesizing, and self-evaluation (after essay completion) marks the end of phase synthesizing. Figure 6 illustrates the difference in these three measures over time, which suggests a differential judgment about students' ability to answer the question during the online inquiry task. While students' judgment about their ability to answer the research question drops rather linear in the Expert-Modeling group, students in the Control group seem to drop at a faster pace during phases searching/evaluating. Furthermore, the students in the Control group's judgment about their ability to answer the question, realigned to the same level of the Expert-Modeling group after completion of the essay.

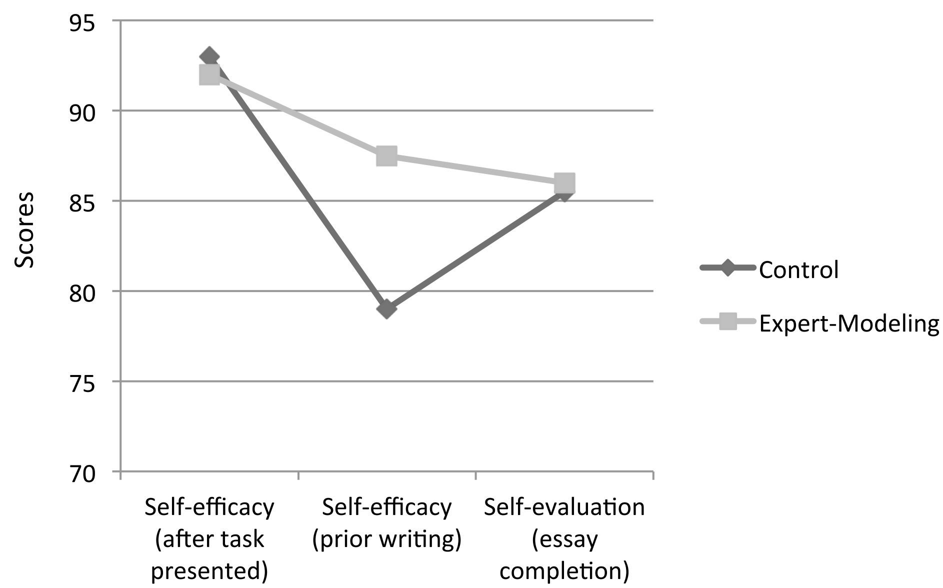


Figure 6. Students' self-efficacy and evaluation prior and after phases searching/evaluating and synthesizing

In order to statistically show differences between the Expert-Modeling and Control group over these three data points, a repeated measures general linear model analysis was performed. The data was recoded with the three measures of students' judgment of their ability to answer the inquiry question (self-efficacy after task presented, self-efficacy prior to writing the essay, and self-evaluation after essay completion) as the within-subject factor, and group as the between-subject factor. The results confirmed the above observation by showing a significant multivariate within-subjects main effect for students' judgment of their ability to answer the inquiry question, $F(2, 38) = 6.56$,

$p < .05$, $\eta_p^2 = .15$. In addition, a quadratic interaction effect was found to be significant for within-subject ability judgment and group, $F(2, 38) = 4.66$, $p < .05$, $\eta_p^2 = .05$, showing differential group differences across the three levels of students' ability judgment.

Impact of strategy instruction on categorical key self-regulatory measures.

Since some of the key self-regulatory measures have been coded categorically, Chi-square (χ^2) tests of independence were used to determine any group differences on these categorical variables: goal setting, planning, and attributions. Table 2 shows the frequency counts for all three categorical variables by group. The results of the Chi-square (χ^2) analysis for planning revealed a significant difference between the two treatment conditions, χ^2 (2) = 12.76, $p < .05$, with the Expert-Modeling group showing more structured planning during the forethought phase than students in the Control Group.

Table 2.

Frequency counts of categorical variables by experimental condition

Variable	Category	Control	Expert-Modeling	Total
Planning*	Structured	3	12	15
	Somewhat structured	7	7	14
	Unstructured	10	1	11
Goal Setting	Process	5	10	15
	Outcome	9	8	17
Attribution*	Task Difficulty	11	2	13
	Personal Ability	9	18	27

*p < .05

By looking at Table 2, it can be seen that students' task planning in the Expert-Modeling group was significantly more structured (12) compared to students in the control group (3). Conversely, students in the control group (10) were significantly more unstructured during planning than their Expert-Modeling counterparts (1).

In addition, it can be seen that the students significantly differed in their causal attributions, χ^2 (1) = 9.23, $p < .05$, where students in the Expert-Modeling group attributed failure to answer the question to personal ability, and students in the Control group to task difficulty. There were no significant group differences in students' goal setting, χ^2 (1) = 2.5, $p > .05$.

Students' Calibration During Online Inquiry (Hypothesis 3)

A logical next step was to look at whether the intervention impacted positively on how well students in the Expert-Modeling group were able to judge their ability to answer the inquiry question (hypothesis two) in relation to their actual essay scores (hypotheses one). In order to capture the dynamic nature of students' calibration at specific points during the online inquiry (following the same rationale as during the analysis of hypothesis two), mean bias scores were calculated for the variables self-efficacy (when inquiry task was presented), self-efficacy (prior to writing the essay), and self-evaluation (after essay completion).

Following hypothesis three, another two-group MANOVA comparison was conducted in order to investigate whether students in the Expert-Modeling group were better able to calibrate their judgments of predicted outcomes of self-efficacy (after inquiry task was presented and prior to writing the essay) and self-evaluation (after competing the essay) with actual outcomes than students in the Control group. The dependent measures for the analysis were mean bias scores of self-efficacy (after inquiry task was presented and prior to writing the essay) and self-evaluation (after selection of key sentences). These scores were calculated by subtracting students' outcome scores (rescaled from a maximum score of 12 to 100) from the scores of the respective measures above. The multivariate effect showed a significant result, $F(1, 39) = 3.01$, $p < .05$. Figure 6 shows the mean bias scores for the respective variables by group. It can be seen that mean bias scores for all measures in both groups were positive, indicating that students in both groups over-estimated their performance substantially, with scores ranging from 24.14 (self-evaluation after essay completion) to 41.17 (self-efficacy after inquiry task was presented).

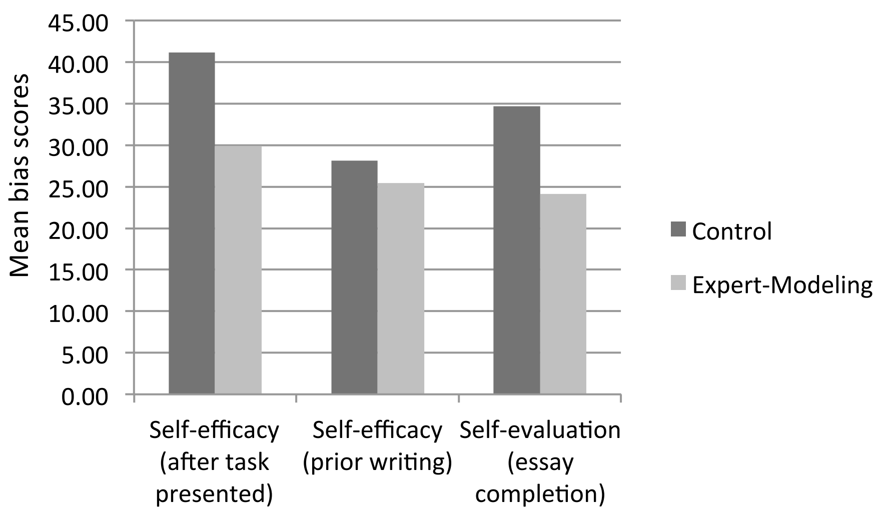


Figure 7. Mean bias scores for self-efficacy and self-evaluation

To better interpret the significant results of the MANOVA, subsequent univariate t-tests were conducted to determine whether significant differences between Expert-Modeling and Control group were present across all three data points. The results of the univariate t-tests showed that mean bias scores for self-efficacy (after inquiry task was presented) differed significantly, $F(1, 39) = 4.34$, $p < .05$, $\eta_p^2 = .10$, with the Expert-Modeling group ($M = 29.92$, $SD = 24.19$) displaying less bias than the Control group ($M = 41.17$, $SD = 16.51$). Similarly, the results showed a significant difference in mean bias scores for self-evaluation after writing the essay, $F(1, 39) = 4.27$, $p < .05$, , $\eta_p^2 = .10$, with the Expert-Modeling group ($M = 23.91$, $SD = 20.45$) being better calibrated than the Control group ($M = 34.67$, $SD = 16.29$). The groups did not significantly differ on the mean bias score for self-efficacy prior to writing the essay, $F(1, 39) = .42$, $p > .05$, $\eta_p^2 = .01$.

Whereas prior research has shown gender differences in students' calibration during learning in CBLEs (Noel, 2002; Hadwin et al., 2007), differences during open online inquiry tasks have not yet been investigated. In order to determine whether there were any gender differences in students' calibration, a subsequent MANOVA of mean bias scores of self-efficacy (after inquiry task was presented and prior to writing the essay) and self-evaluation (after selection of key sentences) as dependent measures was performed. The multivariate effect showed a significant result, $F(1, 39) = 3.82$, $p < .01$. Subsequent univariate t-tests showed that mean bias scores for self-efficacy (after inquiry task was presented) differed significantly, $F(1, 39) = 7.86$, $p < .05$, , $\eta_p^2 = .17$, with males ($M = 49.17$, $SD = 17.21$) overestimating at a higher level than females ($M = 30.12$, $SD = 20.61$). Similarly, mean bias scores for self-efficacy prior writing the essay differed significantly, $F(1, 39) = 8.7$, $p < .01$, , $\eta_p^2 = .19$, with males ($M = 39.17$, $SD = 17.29$) having higher bias than females ($M = 21.19$, $SD = 17.81$). And lastly, mean bias scores for self-evaluation after writing the essay also differed significantly, $F(1, 39) = 8.7$,

$p < .05$, $\eta_p^2 = .10$, with males ($M = 38.33$, $SD = 19.61$) being less calibrated than females ($M = 25.12$, $SD = 17.80$).

Multivariate Regression Analysis

To investigate the predictive power of all nine cognitive key-self-regulatory measures, a combined analysis (one scale) of these measures was performed to predict students' writing skill during online synthesis. In order to transform the metric measures to a 0 to 1.00 scale, prior knowledge about subject matter, perceived instrumentality, perceived intrinsic interest, self-efficacy beliefs and self-evaluation measures were divided by 100. In addition, essay scores were divided by 12. The categorical variables goal setting, planning and attributions were dummy coded. For goal setting, "1" indicated the presence of the key-self-regulatory process, and "0" did not. The three levels of the variable planning (unstructured, somewhat structured, structured), were recoded into three dummy variables, where "1" indicated the presence of the key-self-regulatory process, and "0" did not. Attribution scores were dummy coded where "0" referred to attributions of task difficulty and "1" referred to attributions of personal ability. The multivariate regression of all nine key self-regulatory measures on the writing skill revealed no significant predictors of the overall model, which was not significant, $R^2 = .36$, $F(9, 31) = 1.68$, $p > .05$.

Despite these sobering results, a closer examination of all key self-regulatory variables was conducted to determine if any of the predictor variables alone are predictive of the actual outcome score. Table 3 shows zero-order correlations among all independent metric measures. Significant correlations were found between self-efficacy prior to writing the essay and self-evaluation after writing the essay ($r = .68$, $p < .01$), and self-efficacy prior to writing the essay and the essay score (*r* = .37, *p* < .05). The remaining correlations were non-significant and fairly low, ranging from *r* = -.16 to *r* = .27.

Table 3.

Correlation Matrix for Key Self-regulatory Processes and Essay Score

	1	2	3	4	5	6	7
1. Perceived instrumentality	–						
2. Knowledge subj. matter	-0.02	–					
3. Intrinsic interest	-0.11	0.11	–				
4. Self-efficacy (task presented)	-0.16	0.31	0.31	–			
5. Self-efficacy (prior writing)	0.17	0.05	0.21	0.05	–		
6. Self-evaluation (after writing)	0.26	0.10	0.27	-0.03	**0.68****	–	
7. Essay score	0.25	0.18	-0.14	-0.10	**0.37***	0.27	–

*p < .05 **p < .01

In addition to the correlations of the metric measures, correlations between all dummy coded categorical measures were analyzed. The results showed that students' causal attribution was significantly correlated with the essay score (*r* = .43, *p* < .01). The correlations of planning (*r* = .22, *p* > .05) and goal setting (*r* = -.06, *p* > .05) were not significantly related to the outcome score.

Given the fact that both self-efficacy (prior writing) and attribution showed significant correlations with the outcomes scores, it can be assumed that a reduced model may deliver a better fit for the data to significantly predict students' outcome scores. A subsequent step-wise multiple regression, delivered a significant reduced model (R^2 = .32, $F(9, 31) = 5.57$, $p < .05$), with attribution, self-efficacy prior to writing the essay, and planning (structured) as predictor variables. Both attribution (β = .13, $t(36) = 2.5$, $p < .05$) and self-efficacy prior to writing the essay (β = .34, $t(36) = 2.37$), $p < .05$) significantly predicted the outcome scores in this model when controlling for the other two independent variables. Planning did not significantly predict writing scores when controlling for the two other independent variables (β = .06, $t(36) = 1.17$, $p > .05$).

Influences of Expert-Modeling on Actual Self-regulatory Search Strategy Use

The previous analysis looked at relationships of students' cognitive measures at specific points during the online inquiry task, as well as, how these measures relate to the actual outcome scores (short essay). Based on the results of the cognitive measures above, the subsequent analysis investigated the extent at which self-regulatory strategy training influenced students' search behaviors during their online inquiry.

Impact of Topic-Focus strategy on students' selection of search queries.

The first part of the self-regulatory strategy training modeled how students can extract the right search terms from an inquiry question. In order to determine the effectiveness of the intervention, both quantitative and qualitative differences between Expert-Modeling and Control group were examined.

In order to compare differences in the amount of search queries entered into Google, a single factor analysis of variance (ANOVA) was performed. Group means of the amount of search queries entered differed significantly, $F(1, 39) = 39.63$, $p < .05$, η_p^2 = .51,with the Expert-Modeling group (M = 1.3, SD = .66) entering fewer search queries into Google than the Control group (M = 4.45, SD = 2.14). These differences can further be illustrated by looking at the total number of students for each search term entered (see Figure 8). It can be seen that students in the Expert-Modeling group did not go beyond three search terms entered. Most students (n = 16) entered only one search term for their searches. In addition, two students used two and three search terms respectively. Students in the Control group, on the other hand, used up to 9 search terms with 18 students using a minimum of 3 search terms and 7 students a minimum of 5 search terms exemplarily.

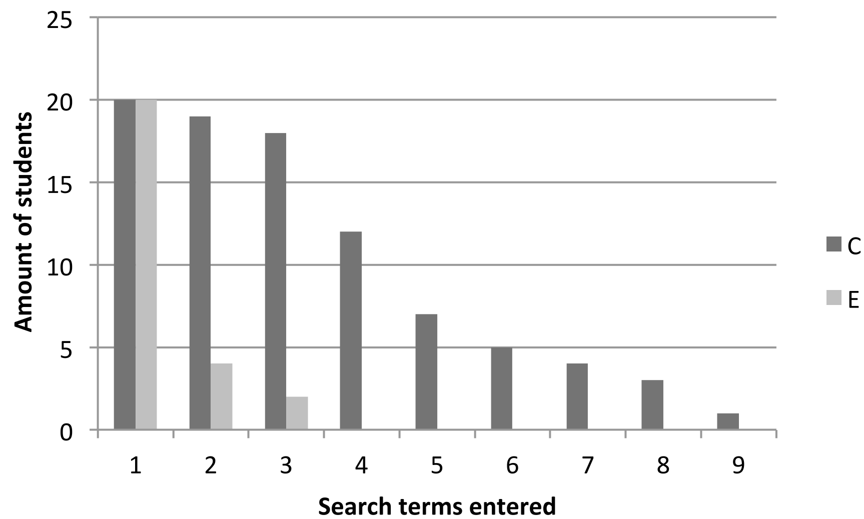


Figure 8. Amount of students for each search term entered

The results of the overall time spent during the phases searching/evaluating showed no significant group differences, $F(1, 39) = 1.22$, $p > .05$, $\eta_p^2 = .03$, in the total amount of time used (in minutes) for all searches between the Expert-Modeling group ($M = 23.70$, $SD = 5.39$) and Control group ($M = 25.60$, $SD = 5.47$). Given that students' in the Expert-Modeling group entered significantly less search queries into Google, a subsequent analysis looked at how much time students in both groups spent on average on the Google results page presented for each search query. Since most students (n = 18) in the Expert-Modeling group did not go beyond entering one search query into Google (Figure 8), a comparison of group means of time spent searching after entering the first search term was performed. Mean differences were significantly different, $F(1, 39) = 36.70$, $p < .05$ $\eta_p^2 = .49$, with the Expert-Modeling group ($M = 21.15$, $SD = 7.48$) spending more time on the first search term than the Control group ($M = 7.4$, $SD = 6.86$). Figure 9 illustrates these results, as well as means for all other search queries that students entered into Google.

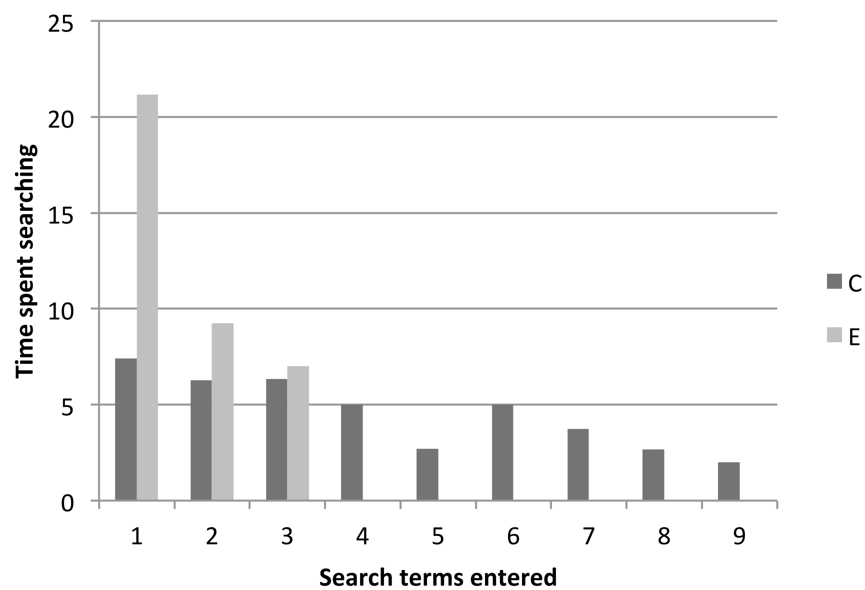


Figure 9. Time spent searching for each search term entered

In addition to the quantitative differences in search patterns during phases searching/evaluating, qualitative group differences of the search queries entered were analyzed by comparing the quality scores on the first search term entered. The results of a single factor ANOVA revealed that group means for the average quality score of the first search term entered was significantly different, $F(1, 39) = 84.21$, $p < .01$, $\eta_p^2 = .69$, with the Expert-Modeling group ($M = 4.05$, $SD = .76$) outperforming the Control group ($M = 1.95$, $SD = .69$). In order to explore the relationship between students' quality scores for the first search term entered and writing score, a subsequent zero-order correlation analysis was conducted. The results showed a significant positive correlation ($r = .37$, $p < .05$) between students' quality scores for the first search term entered and writing scores.

Impact of Metacognitive Monitoring strategy on students' selection of websites.

The second part of the self-regulatory strategy training modeled how students can (metacognitively) determine whether a particular website from the Google results page is trustworthy and (if the answer is yes) whether the website is actually useful in answering the inquiry question. In order to determine the effectiveness of this part of the intervention, both quantitative and qualitative differences between the Expert-Modeling and Control group were examined.

Figure 10 shows the amount of students for each website that was selected for their online inquiry. It is evident that all students in both groups selected at least two unique websites, followed by a sharper drop for students in the Expert-Modeling group compared to students in the Control group. For instance, twice as many students (n = 14) in the Control group than in the Expert-Modeling group (n = 7) selected at least seven websites for their inquiry. Ultimately, students in the Expert-Modeling group selected up to 11 unique websites and students in the Control group selected up to 14 websites.

In order to statistically determine quantitative mean differences in the amount of websites selected from the Google results page, a univariate ANOVA was performed. The results showed significant quantitative group differences, $F(1, 39) = 4.42$, $p < .05$, $\eta_p^2 = .10$, with the Expert-Modeling group ($M = 5.95$, $SD = 2.39$) selecting fewer website for their online inquiry than students in the Control group ($M = 7.75$, $SD = 2.99$).

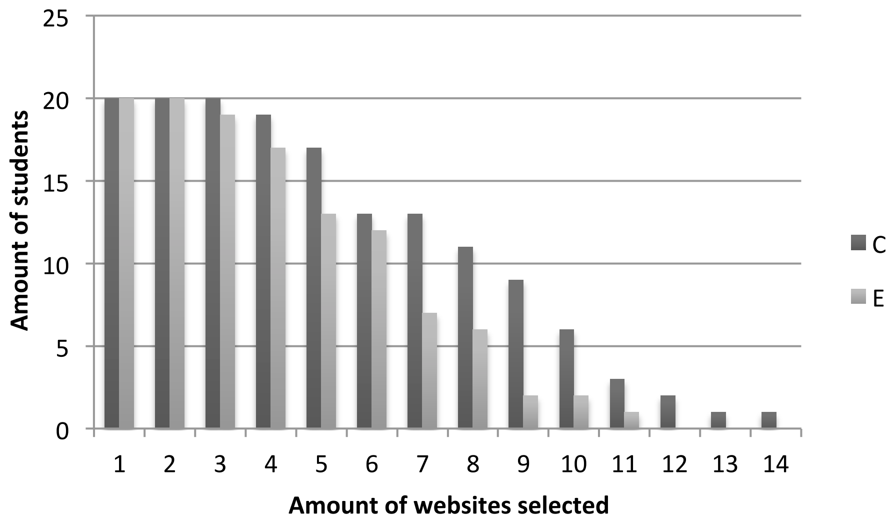


Figure 10. Number of students for each website selected for inquiry

Whereas the quantitative group differences indicate that students in the Expert-Modeling group needed fewer websites to answer the inquiry question, the subsequent analyses looked at the overall quality of the websites selected for inquiry with regards to their usefulness to answer the inquiry question. Given the fact that students in Expert-Modeling group outperformed students in the Control group, it can be hypothesized that the websites selected for inquiry in the Expert-Modeling group are of a significantly higher quality. Since the quality scores for the websites were coded categorically, two Chi-square (χ^2) tests for independence were used to determine whether there are qualitative differences between the Expert-Modeling and Control group. Table 4 shows frequency counts of level of quality (useful, somewhat useful, not useful) by experimental condition; where each group was separated into two sub-groups based on whether or not they actually selected information from the respective websites for their inquiry.

Table 4.

Frequency counts of quality level of websites selected or not selected for inquiry by group

	Selected for Inquiry*		Not Selected for Inquiry	
	Control	Expert-Modeling	Control	Expert-Modeling
Useful	32	29	18	15
Somewhat	46	21	13	6
Not useful	39	45	6	3
Total	117	95	37	24

*p = < .05

Whereas the results showed no significant difference in the quality of websites that have not been used for the inquiry (website selected from results page but no information was clipped to the Zoho notebook), a significant difference, χ^2 (2) = 7. 70, $p < .05$, was found for quality of websites that were actually selected during the online inquiry (website selected from results page and information was clipped to the Zoho notebook).

Exploratory Analysis of Cognitive Measures During Phases Searching/Evaluating

Lastly, exploratory analyses were conducted to investigate differences in self-efficacy and self-evaluation scores during the phases searching/evaluating of students' online inquiry. As outlined in the methods section, students were asked a self-efficacy question immediately after they selected a website from the Google results page for their inquiry. Upon leaving a website, the students were asked a self-evaluation question. This fine-grained data structure of these cognitive measures during phases searching/evaluating allowed for a closer examination of students' searches and search patterns. Since self-regulation may not only impact on the midpoints of scores, but also influence the variation of the scores (B. J. Zimmerman, personal communication, October 26, 2010), the subsequent analyses compared both students' mean scores and means of variances for both self-efficacy and self-evaluation for the selected websites. It can be hypothesized that students in the Expert-Modeling group will reduce the amount of variation during their online inquiry by taking advantage of the self-regulatory strategy training. In other words, self-regulated students should show less variation in their self-efficacy and self-evaluation judgments as they select websites during their online inquiry.

In order to statistically investigate the above research questions of students' variation for self-efficacy and self-evaluation scores, univariate one-way ANOVAs were conducted to compare means and variances between the two groups. To meaningfully interpret these scores, students who selected less than 3 websites for their inquiry were not considered for this analysis. The new sample ($n = 35$) comprised of 19 students in the Control group and 16 in the Expert-Modeling group.

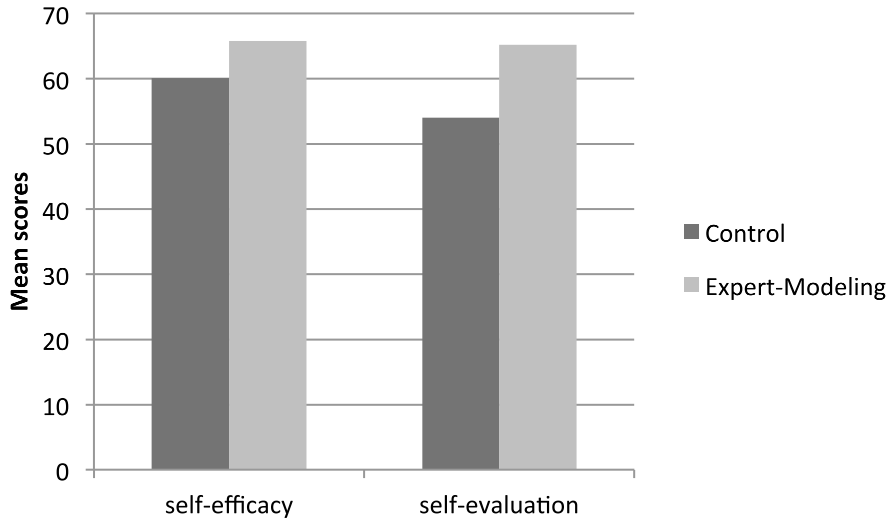


Figure 11. Mean scores for student's self-efficacy and self-evaluation during searching/evaluating

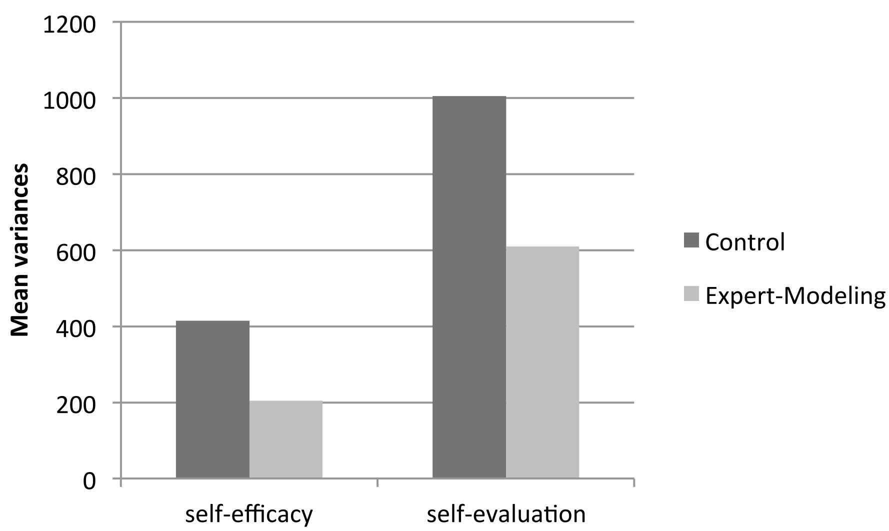


Figure 12. Mean variances for student's self-efficacy and self-evaluation during searching/evaluating

To compare group means on both measures, two univariate one-way ANOVAs were conducted (see Figure 11). Whereas the results revealed no significant group differences for self-efficacy means ($M_{Control}$ = 60.10, $SD_{Control}$ = 11.02; $M_{Expert\text{-}Modeling}$ = 65.82, $SD_{Expert\text{-}Modeling}$ = 13.08), $F(1, 34) = 1.97$, $p > 0.5$, $\eta_p^2 = .06$; self-evaluation means differed significantly, $F(1, 34) = 4.64$, $p < 0.5$, $\eta_p^2 = .12$, with the Expert-Modeling group (M = 65.25, SD = 16.63) showing higher self-evaluation mean scores than the Control group (M = 54.00, SD = 11.69).

To determine whether the groups differed in their variation of judgments about the websites that were selected for inquiry, group means of variances of students' self-efficacy and self-evaluation scores for the selected websites were analyzed using two one-way univariate ANOVAs. The results, as illustrated in Figure 12, showed significant differences in means of students' variances for self-efficacy, $F(1, 34) = 7.79$, $p < .01$, $\eta_p^2 = .19$, with students in the Control group (M = 414.73, SD = 259.84) having higher variances than students in the Expert-Modeling group (M = 205.07, SD = 163.59). Similarly, means of students' variances of self-evaluation also differed significantly, $F(1, 34) = 7.81$, $p < .01$, $\eta_p^2 = .19$, with the Control group (M = 1004.91, SD = 461.06) showing higher variation among scores than the Expert-Modeling group (M = 610.37, SD = 354.86). These findings confirm the above hypotheses, showing that students who did receive the self-regulatory strategy training showed more consistent search patterns (low variances) during their online inquiry, compared to students in the control group (high variances).

CHAPTER FIVE

DISCUSSION

The present study investigated the impact of Expert-Modeling of a self-regulatory strategy in an open online inquiry learning environment (Google) on students' performance, the role of key self-regulatory measures, and calibration (accuracy of performance judgment) during the online inquiry phases searching/evaluating, and synthesizing. Theory-driven data for the study were gathered by employing both microanalytic and trace data methods.

Essay Score (Hypothesis 1)

It was hypothesized that students who receive self-regulatory strategy instruction through Expert-Modeling and guided practice will be able to perform better in an open online inquiry task using the Google search engine. The results showed a positive effect of expert-modeling on students' achievement (writing scores), confirming Schraw's (2007) notion that modeling of self-regulation will help students to better organize and elaborate new information. In addition, the results built on Graesser et al.'s (2007) suggestion to develop better training and metacognitive scaffolding tools during online inquiry to improve students' ability to access reliable and useful information.

Microanalytic Measures of Self-regulatory Processes

Differences on self-regulatory measures (Hypothesis 2).

Regarding hypothesis two, the study investigated the effects of expert-modeling on key self-regulatory measures during online inquiry. Although, the results did not show any significant differences between the six metric measures: prior-knowledge, perceived instrumentality, perceived intrinsic interest, self-efficacy beliefs (when task was presented and prior to writing the essay) and self-evaluation (after writing the essay), self-efficacy (prior to writing) did vary in a marginally significant way ($p = .10$) between the two groups.

As stated above, these measures (individually) did not capture the cyclical and dynamic quality of these key-self-regulatory processes, and a more detailed examination was needed at specific points during their online inquiry: Self-efficacy (when inquiry task was presented) marks the beginning of the phase searching/evaluating, self-efficacy (prior to writing the essay) separates phases searching/evaluating and synthesizing, and self-evaluation (after essay completion) marks the end of phase synthesizing. Upon closer examination and by combining these three measures of students' judgment about their ability to answer the inquiry questions, a main effect was found for a decrease in students' judgment about their ability to answer the inquiry question. These patterns are consistent with previous research (Azevedo et al., 2006), where students' self-efficacy decreased in CBLEs as a function of time.

In addition, a significant interaction effect showed that these judgment scores varied differentially as the students went through the various phases of the inquiry cycle (Figure 6). In other words, although students in both groups entered (self-efficacy after task presented) the inquiry task at a similar level, students' self-efficacy judgment prior to writing the essay (which separates the inquiry phases search/evaluating and synthesis) dropped significantly lower for students who did not receive the Expert-Modeling treatment. Unexpectedly, students' self-evaluation scores realigned in both groups to the same level by the time they have finished their essay. This pattern may be indicative that students, who did not receive the Expert-Modeling instruction, may have experienced some difficulties or metacognitive challenges (Quintana et al., 2005) during the phases searching/evaluating. Students' self-evaluation judgment about their essay may not necessarily account for these challenges since the study separated searching/evaluating from the actual writing task during which no more web searches were allowed.

The results also showed significant differences on the categorical key self-regulatory variables planning and attribution (Table 2). Students who received the Expert-Modeling treatment articulated more structured levels of planning activity during the asking questions phase of the inquiry cycle, which conforms to Zimmerman's (1998, 2000) forethought phase. In addition, students' in the Expert-Modeling group attributed their performance to personal ability, whereas students in the control group attributed their performance to task difficulty. These causal attributions show that students, who have been explicitly trained to use a self-regulatory strategy, perceive themselves as empowered and being in charge of their learning, and subsequently did not attribute their performance to the difficulty of the given task (Zimmerman, 2008a).

Students in both groups generally indicated that they set goals for themselves. Upon closer examination, however, the data revealed two emerging patters between the two groups. Whereas students who set goals without any self-regulatory strategy training set more outcome goals, students who did receive self-regulatory strategy training set more process goals. Although these last results did not yield any significant differences, they seemed to be directive of the interplay between goal setting during the forethought phase and their influence on attributional causation during the self-reflection phase;

which may in turn lead to sustained cyclical self-regulating in subsequent learning efforts (Zimmerman, 2008a).

Calibration during online inquiry (Hypothesis 3).

It was hypothesized that students who received self-regulatory strategy training through Expert-Modeling and practice, were better able to calibrate their judgment of predicted outcomes of self-efficacy (after inquiry task was presented and prior to writing the essay) and self-evaluation (after essay completion) with their actual performance on the essay. The results (see Figure 7) show that students were universally positively biased about their performance at these three measuring points during their inquiry, with students who received no self-regulatory strategy training being significantly more overconfident when entering (self-efficacy after task was presented) and exiting (self-evaluation after essay completion) the online inquiry task. The two groups did not significantly differ in their calibration after completing the inquiry phase searching/evaluating.

In addition to group differences in students' calibration, the study also confirmed Noel's (2002) finding that males were significantly more overconfident than females across all three measures of mean bias scores. Both findings of students' calibration in an open online inquiry environment expand on the results of students' positive bias in closed CBLEs (Noel, 2002; Hadwin et al., 2007).

Self-regulation scale for online inquiry.

A multivariate analysis of all nine key-self-regulatory measures, following Zimmerman's (1999) approach, did not yield an overall significant model for self-regulation. This may be attributable to low correlations among most independent metric measures; except for significant positive correlations between self-efficacy (prior writing), self-evaluation (after writing) and essay score respectively (Table 3). A reduced, yet significant model, which included planning, self-efficacy (prior writing) and attribution as its main predictors, provided a better fit for the data. It should be noted at this point that this reduced model included variables that showed significant differences between the two treatments conditions; namely, planning, self-efficacy prior to writing, and attribution. Although a causal relationship was established during the analysis of the data, these results lend itself to be explained within Zimmerman's (2000) framework, in that students who performed higher on an inquiry task (1) were more structured in their planning during the forethought phase, (2) had higher self-efficacy during the performance phase, and lastly (3) attributed their performance towards their own ability during self-reflection.

Influences of Expert-Modeling on Actual Self-regulatory Search Strategy Use

Impact of Topic-Focus strategy on students' selection of search queries.

A key component of the self-regulation strategy was the selection of a topic and the focus from an inquiry question (Eagelton & Dobler, 2007). The results of this study showed that students who received self-regulatory strategy instruction through Expert-Modeling almost uniformly entered one search term into the Google search engine during their online inquiry, spending almost all of their allocated time on the Google results page that this search term delivered. In contrast, students who did not receive any instruction were less strategic in their search approaches and entered multiple search queries into the search engine; consequently spending less time on average on the results page for each search query entered. Illustratively, students in the latter group entered up to nine search queries (Figure 8) during the inquiry, with most students needing at least three search queries for their inquiry. This pattern of switching search queries or trying new search terms can be interpreted as adaptive (possibly maladaptive due to lower outcome scores) behavior to unsuccessful searches, since the results page (computer generated feedback) did not provide the students with the appropriate information to answer the inquiry question. This search behavior is also reflective of what Guinee et al. (2003) identified as a reactive approach to unsuccessful searches. Students in the Expert-Modeling group, on the other hand, largely did not change their search queries indicating a more proactive and strategically planned search approach during their online inquiry. This notion can be further substantiated by looking at the quality of search queries that the students used for their searches. The results showed that students in the Expert-Modeling group entered significantly qualitatively higher search terms than students who did not receive self-regulatory strategy instruction. In summary, these findings lend themselves to a causal interpretation in that better search terms, yield better search results from the onset, which in turn may not require any adaptive behavior to improve the results. Future research may look into models to quantify these assertions.

Impact of Metacognitive Monitoring strategy on students' selection of websites.

Of particular interest to this study was a closer examination of the websites that the students selected during their online inquiry. Since the second part of the self-regulatory strategy involved metacognitive support to help students determine the reliability and usefulness of websites, both quality and quantity of selected websites were hypothesized to differ between the groups (Eagelton & Dobler, 2007).

The results showed that students in the Expert-Modeling group significantly selected fewer websites during the inquiry phases searching/evaluation. As can be seen in Figure 9, all students selected at least two websites from the results page during their online inquiry, followed by a steeper drop for students who did not receive the self-regulatory strategy training. This difference can be interpreted to mean that students in the Expert-Modeling group were more selective during the searching/evaluating phase.

The quantitative difference in number of websites selected from the results page needed some further elaboration by comparing the qualitative nature of these websites between the two groups; especially with regards to students' monitoring processes of whether the websites under investigation have been deemed useful, or not. The results did not show any significant group differences in the number of websites that have not been selected for further inquiry (information clipped to notebook). Students in the Expert-Modeling group, however, did clip information from more qualitatively higher (more useful) websites than did students in the Control group. In summary, these results showed that metacognitive monitoring as part of a self-regulatory strategy helped students in the Expert-Modeling group to better evaluate websites during online inquiry. On the contrary, students who did not receive self-regulatory strategy training, were not as successful in selecting qualitatively higher websites from the Google results page (computer generated feedback). As suggested by Lajoie (2008), this feedback, which is internal in nature and dependent on a monitoring process to evaluate one's performance (Lajoie, 2008), did not have the power to initiate qualitatively better selections of these websites in the Control group (as suggested by Proske et al., 2007; Azevedo, 2008).

Exploratory Analysis of Cognitive Measures During Phases Searching/Evaluating

The last part of this study was an exploratory analysis in order to investigate whether students in both groups showed differences in patterns of self-efficacy and self-evaluation for each selected website during their inquiry. Following Moos and Azevedo's (2009b) suggestion, the microanalytic measures employed of this study helped to measure self-efficacy at multiple points during learning. Expanding on this, the present study also included measures for self-evaluation in order to be able to measure students judgment about the usefulness of a website at the points of entry (self-efficacy) and the point of exit (self-evaluation).

While the cognitive data for self-efficacy and self-evaluation for each website selected, represented a fairly complex structure, an analysis of a hierarchical multilevel model did not seem feasible; especially with regard to cognitive measures as indicators for varying search patterns, and patterns of adaptations to unsuccessful searches and websites that were judged not useful for the online inquiry. A statistical consulting session (D. Rindskopf, personal communication, September 28, 2010) suggested looking at the data at the level of the individual student by comparing both means and variances between the two groups. Similarly, Zimmerman (personal communication, October 26, 2010) suggested taking a closer look at both group means and mean variances since self-regulation may not only impact on the midpoints of scores, but it may also influence the variation of the scores. Whereas the results revealed no significant group differences for self-efficacy scores, means for self-evaluation differed significantly. The non-significance of group differences for students' self-efficacy means, can suggest that students in both groups may not have been fully able to determine the usefulness of a particular website at the level of the Google results page, which includes both website title and a brief two-line abstract with bolded search terms. However, once students were able to access and evaluate the webpage more closely by entering the page, their ability to judge the usefulness improved significantly in the Expert-Modeling group. Inversely, lower average scores for students in the Control group may be attributed to students' inability to accurately evaluate whether websites are actually useful (or not).

In order to further investigate these patterns, a comparison of students' variances of their self-efficacy and self-valuation scores showed that variances for students in the Expert-Modeling group were significantly lower compared to students in the Control group. The lower variation among all of these measures showed that students who were metacognitively monitoring the truthfulness and usefulness of websites during online inquiry, seem to be more consistent and successful in their searches and search patterns; thus being more self-regulated.

Educational Implications

While Kaufmann (2008) showed how metacognitive prompts during a complex web-base learning task helped students to write with more clarity, the results of this study showed that these metacognitive prompts can be conveyed through Expert-Modeling and guided practice prior to an online inquiry task, thus not relying on conceptual scaffolds or metacognitive prompts during online learning tasks. This notion has been emphasized by Winters et al. (2008), who noted that in order to truly be able to talk about the acquisition of a self-regulatory skill, scaffolding and support tools may have to be removed at some point. As such, Zimmerman's (2000) social multilevel model of self-regulatory development, proved to be effective in helping students to acquire a self-regulatory skill in order to be able to navigate the Internet during online inquiry more efficiently.

As such, potential implications for these findings could result in a more targeted approach to help – especially – community college students to overcome certain (metacognitive) challenges during online research. In particular, both cognitive and metacognitive scaffolding strategies (such as the ones used in this study) may help these students to determine whether the information provided by search engines actually trustworthy, as well as, useful to support an answer to a particular inquiry question. I hope that self-regulatory strategies instruction through modeling and guided practice, will become part of every introductory course that deals with online research, in order to provide students with more useful tools that will empower them to manage and organize the information that is available online. In addition, these types of interventions will further help students who consistently overestimate their self-regulatory functioning when doing online research, despite their actual ability and skills level. This notion has been highlighted in a recent interview (Bembenutty, 2008), where Zimmerman pointed out that this problem of "low calibration" is especially prevalent among at-risk students. He further emphasized that "expert learners are less optimistic but more accurate in their calibration than novices" (p.180). As such, it may be even more important to address these issues fairly early on in students' education, in order to help them better access and learn from information online, which, given its wealth of recourses, becomes increasingly difficult to navigate.

Limitations of Study and Future Research

A possible limitation of this study is its small sample size, its generalizability to other populations, CBLEs and tasks, as well as its limited scope by not measuring SRL in its entirety. For instance, the students did not receive feedback on their essay scores during the self-reflection phase, which according Zimmerman's (2000) cyclical SRL model would help inform students' forethought phase in a subsequent online inquiry. In addition, it should also be noted that the phase searching/evaluating and synthesis are often carried out simultaneously during students' online inquiry. The study was conducted in a laboratory setting, which minimizes the role of possible in-classroom influences, such as peer-support and other forms of help-seeking.

The results of this study provide several interesting openings to further explore the role and interplay of self-efficacy and self-evaluation beliefs at important junctures during students' online inquiry; especially within the context of students' calibration at a more granular level (such as search terms entered and websites selected). In addition, further research is needed to determine the role of feedback (on outcome scores) during the self-reflection phase (Zimmerman, 2000) on students' forethought phase in future inquiry tasks. An investigation of these recursive feedback loops can help to determine the impact on students' self-regulation during subsequent online inquiry tasks over an extended period of time. And lastly, future research may look into how additional metacognitive strategies can help to improve students' adaptation to unsuccessful searches and calibration during online research.

Conclusion

The present study showed that self-regulatory strategy instruction through modeling and guided practice helped students to better perform during an open online inquiry task using Google. Furthermore, the combination of both micro-analytic measures and trace data demonstrated a new way of investigating self-regulation in CBLEs, especially with regard to the dynamic nature of self-regulation and its relation to actual learning outcomes. While the study gives a fairly comprehensive overview of students' self-regulatory behavior during online inquiry at multiple levels, it lends itself to further exploration as to (1) why students universally overestimate their performance and (2) what metacognitive strategies may help students to better calibrate their performance during the phases searching/evaluating.

APPENDIX

Appendix A

Narrative for Google and Zoho Notebook training video:

Part I: Intro Google

By using the Google search engine, you can access information on the Internet by entering the words or phrase that best describe the information you want to find. These search terms are also called search queries.

The most important field of the Google search engine is the search field. To do a search on Google, just type in a few descriptive search terms. Let's try to look up information about the "solar system."

Now, hit the 'Enter' key or click on the "Google Search" button.

As you can see, Google produces a results page, which is a list of web pages. This page can often span over multiple pages.

Our search results page is packed with information related to your search term "solar system." It is important to know that the most relevant page is appearing first, followed by the most second important, and so on.

Now, let's have a look at the all the information that this page provides.

The first line of any search result item is the title of the web page that we found.

The text below the title is an excerpt from the results page with your query terms bolded.

You can also see the web address (or URL) of where the information is located.

To access the content of a website, simply click on a link of one of the search results. To go back to your search results, click on the "back" button in your browser.

You can now select a different search result from the page, or enter a new search query.

Part II: Intro Zoho Notebook:

It is not always easy to keep track of all the searches, search results and related content.

With Zoho Notebook, you can browse, clip, and organize information from across the web in a single online location that is accessible from any computer.

You can open and close the mini Zoho Notebook by clicking the notebook icon in your browser's status bar.

Let me now show you how to do that:

After you read the content of a website, simply highlight the content that interests you and add these clippings to your notebook by clicking on the star button in your mini notebook.

After you added clippings of web content to your notebook, you can also add comments or paraphrase the text. Just click the Comment link below the note where you want to add a comment.

You can also organize your notes quickly and easily from the full-page view.

Simply rearrange your notes by dragging and dropping them from one section to another. Of course, you can also add some more comments to your clippings or paraphrase your findings.

Appendix B

ID#: ___________________
Date: ___________________

Practice Sheet: Google and ZohoNotebook

Open the Firefox web browser and complete the following exercise to better familiarize yourself with Google and the Zoho Notebook function:

(1) Open the Zoho mini Notebook (bottom right corner of status bar),
(2) Select a website of your choice (e.g. www.nytimes.com),
(3) Skim-read through website,
(4) Highlight important information,
(5) and clip information to notebook,
(6) **Repeat** steps 1 through 5 **five times**, and
(7) Open Notebook in full-page review your clippings.

Appendix C

Narrative for expert strategy-modeling video (Part 1)

When looking for some specific information online it is not always easy to determine the right search terms or search queries for a particular inquiry question. Let's try to determine the right search term for a search about the history of our solar system. People often make the mistake of selecting search terms that are simply too broad, such as "solar system." Or, they are too wordy, such as "What is the history of our solar system?" The truth lies somewhere in the middle. A query that would be just right could be "solar system" + history.

The last search terms are better because they have both a TOPIC and a FOCUS, whereas the TOPIC in this example is "solar system," the FOCUS is "history." A great and easy way to identify TOPIC and FOCUS is to use the following strategy:

1. Circle TOPIC of the Inquiry Question.
2. Underline FOCUS, or focuses, of the Inquiry Question.
3. Create Search Terms (TOPIC + FOCUS)

Alright, let me now show you a couple of examples of how this strategy can be applied.

The first application refers to literal questions, meaning that all search terms can be found directly in the question. Let's try to find TOPIC and FOCUS of the question

How many planets does our solar system have?

I can see that the term solar system provides my topic, let me circle that, and that planets are my focus (underline "planet"). In other words, I am looking at a broad category, solar system, and "zoom-in" on a specific aspect of this category, my focus "planets."

Query: "Solar System" + planets

Inquiry questions often have more than one focus. In the following example we can see again that "solar system" is our topic and that we have a double focus, namely "planet" and "moon."

Double Focus Area: What planets of our solar systems have moons?
Query: "solar system" + planet + moon

Narrative for expert strategy-modeling video (Part 2)

One of the most difficult tasks when doing research online is to investigate whether you can trust the information on a website or not. Unlike in the library, where you can ask at the reference desk about where to find "good" resources, online, you are on your own and it is important that you are aware of how you can check the truthfulness of your search results.

A results page can sometimes be overwhelming and it requires some practice to determine whether a particular website will help you to answer a question of interest. Although Google does a fairly good job in sorting out good from bad search results (with the most relevant page on top), you still need to ask yourself the following two questions when looking at the URLs presented on your results page:

(1) Is the site trustworthy? Why or why not?

To answer this question, take a look at the website title to investigate whether the site is from a trusted source (NASA, National Geographic, etc…). In addition, domain names, such as .gov (government), .org (non-profit and research organizations), or .edu (education), can be a clue to the reliability of the host. Once you believe that the title and URL indicate that the website is from a trustworthy source, ask yourself:

(2) Does the site match my inquiry question? Why or why not?

Now, take a close look at the description of the website and how your bolded search terms have been used in this brief abstract. If you believe that the site matches your inquiry question, you can move forward and dive a little deeper into the website by skimming through the information presented on the selected webpage. Similar to the questions above, you will now have to answer for yourself:

(1) Is the information on the site still trustworthy? Why or why not?
(2) Does specific information on the site match my inquiry question? Why or why not?

Once you are able to answer both questions with YES, you have successfully located information that matches and, most importantly, will help you to answer your inquiry question. You can now select/highlight the respective passage and clip it to your notebook.

As soon as you have collected enough information from this trustworthy site, you may go back to the results page and continue with your inquiry.

Appendix D

ID#: ___________________
Date: ___________________

Expert Modeling Practice Sheet (Part 1): TOPIC + FOCUS Strategy

1. Circle TOPIC(s) of Inquiry Question(s)
2. Underline FOCUS, of focuses, of Inquiry Question(s)
3. Create Search Terms (TOPIC + FOCUS)

A. Literal Questions

QUESTION	TOPIC	FOCUS
1. Who is the inventor of basketball?		
2. How many directors did *Shrek I* have?		
3. In which country is Mount Everest?		

B. Double Focus Questions

QUESTION	TOPIC	FOCUS
1. What is the most popular girl's name in the United States?		
2. In what year did women gain the right to vote in America?		
3. Who was the first African American to win the Nobel Prize for Literature?		

Answer Key:

A1 – basketball (T) + inventor (F)
A2 – Shrek I (T) + directors (F)
A3 – Mount Everest (T) + country (F)
B1 – Popular name (T) + girl (F) + United States (F)
B2 – Vote (T) + women (F) + year (F) or America (F)
B3 – Nobel Prize (T) + literature (F) + African American (F)

Expert Modeling Practice Sheet (Part 2): Evaluating Truthfulness of Websites

Identify a keyword from part 1 of this practice sheet and type the search terms into your Google search field. Then select the first link to closely analyze. All of the information you need should be collected from the results page.

(1) Is the site trustworthy?

Title: ____
URL: ____
Trustworthy: ❏ YES ❏ NO
Why or why not?

If you answered the question about trustworthiness with NO, select the next website, if you checked YES, move on to question (2)

Title: ____
URL: ____
Trustworthy: ❏ YES ❏ NO
Why or why not?

(2) Does the site match my inquiry question?
Now, take a close look at the description of the website and how your bolded search terms have been used in this brief abstract.

Match: ❏ YES ❏ NO
Why or why not?

If you answered this question with YES, you can move forward and dive a little deeper into the website by skimming through the information presented on the selected webpage. Similar to the questions above, you will now have to answer for yourself:

(1) Is the information on the site still trustworthy?

Trustworthy: ❏ YES ❏ NO
Why or why not?

(2) Does specific information on the site match my inquiry question? Why or why not?

Match: ❏ YES ❏ NO
Why or why not?

Appendix E

ID#: ___________________
Date: ___________________

Answer Sheet: Online inquiry task using the Google Search Engine:

Please answer the following research question by accessing information on the Internet using the Google search engine (www.google.com).

How is global warming going to impact on the future of humanity?

Integrate your findings by composing a 250 word written response (approximately ½ page single spaced). You have a total of 60 minutes to complete this task, 30 minutes to search online by using the Google search engine and to clip your findings to the Zoho Notebook and 30 minutes to write your essay.

IMPORTANT:
Please signal (by raising your hand) as soon as you have completed your research and when you are about to start writing your written response in the box below. You are not allowed to incorporate any other information than the information you clipped to your Zoho Notebook.

You must use your own words for your answer!

Type your 250 words written response in the box below:

Appendix F

Essay Scoring Guide

SCORE OF 6
An essay in this category demonstrates clear and consistent mastery, although it may have a few minor errors. A typical essay

- effectively and insightfully develops a point of view on the issue and demonstrates outstanding critical thinking, using clearly appropriate examples, reasons, and other evidence to support its position
- is well organized and clearly focused, demonstrating clear coherence and smooth progression of ideas
- exhibits skillful use of language, using a varied, accurate, and apt vocabulary

SCORE OF 5
An essay in this category demonstrates reasonably consistent mastery, although it will have occasional errors or lapses in quality. A typical essay

- effectively develops a point of view on the issue and demonstrates strong critical thinking, generally using appropriate examples, reasons, and other evidence to support its position
- is well organized and focused, demonstrating coherence and progression of ideas
- exhibits facility in the use of language, using appropriate vocabulary

SCORE OF 4
An essay in this category demonstrates adequate mastery, although it will have lapses in quality. A typical essay

- develops a point of view on the issue and demonstrates competent critical thinking, using adequate examples, reasons, and other evidence to support its position
- is generally organized and focused, demonstrating some coherence and progression of ideas
- exhibits adequate but inconsistent facility in the use of language, using generally appropriate vocabulary

SCORE OF 3
An essay in this category demonstrates developing mastery, and is marked by ONE OR MORE of the following weaknesses:

- develops a point of view on the issue, demonstrating some critical thinking, but may do so inconsistently or use inadequate examples, reasons, or other evidence to support its position
- is limited in its organization or focus, or may demonstrate some lapses in coherence or progression of ideas
- displays developing facility in the use of language, but sometimes uses weak vocabulary or inappropriate word choice

SCORE OF 2
An essay in this category demonstrates little mastery, and is flawed by ONE OR MORE of the following weaknesses:

- develops a point of view on the issue that is vague or seriously limited, and demonstrates weak critical thinking, providing inappropriate or insufficient examples, reasons, or other evidence to support its position
- is poorly organized and/or focused, or demonstrates serious problems with coherence or progression of ideas
- displays very little facility in the use of language, using very limited vocabulary or incorrect word choice.

SCORE OF 1
An essay in this category demonstrates very little or no mastery, and is severely flawed by ONE OR MORE of the following weaknesses:

- develops no viable point of view on the issue, or provides little or no evidence to support its position
- is disorganized or unfocused, resulting in a disjointed or incoherent essay
- displays fundamental errors in vocabulary

Appendix G

Research design and measures

PHASES	SUB-PROCESSES	CONTROL	EXPERT MODELING	COGNITIVE MEASURES	BEHAVIORAL MEASURES
Pre-treatment	Intro to Google (general video and practice)	X	X		
	Intro to Zoho Notebook (general video and practice)	X	X		
Treatment	Modeling of Expert Search Strategy (Observation)		X		
	Guided Practice of Expert Search Strategy (Emulation & Self-Control)		X		
Asking Questions	Prior to inquiry task is presented			Perceived instrumentality	
	After inquiry task is presented			Knowledge about subject matter Self-efficacy beliefs Perceived intrinsic interest Goal setting Planning	
Searching	After entering a new search term			Self-efficacy	Quality and Quantity
Evaluating & reading	After selecting a site			Self-efficacy	Quality and Quantity
	After leaving a website			Self-evaluation	
Synthesizing	Prior to writing written response			Self-efficacy	
	Immediately after completion of written response			Self-evaluation Attribution	Outcome Measure

BIBLIOGRAPHY

Azevedo, R. (2005a). Computer environments as metacognitive tools for enhancing learning. *Educational Psychologist, 40*(4), 193-197. doi:10.1207/s15326985ep4004_1

Azevedo, R. (2005b). Using hypermedia as a metacognitive tool for enhancing student learning? The role of self-regulated learning. *Educational Psychologist, 40*(4), 199-209. doi:10.1207/s15326985ep4004_2

Azevedo, R., & Cromley, J.G. (2004). Does Training on self-regulated learning facilitate students' learning with hypermedia? *Journal of Educational Psychology, 96*(3), 523-535. doi: 10.1037/0022-0663.96.3.523

Azevedo, R., Guthrie, J. T., & Seibert, D. (2004). The role of self-regulated learning in fostering students' conceptual understanding of complex systems with hypermedia. *Journal of Educational Computing Research, 30*, 87-111. doi:10.1007/s11409-007-9014-9

Azevedo, R., Cromley, J. G., Winters, F. I., Moos, D. C., & Greene, J. A. (2006). Using computers as metacognitive tools to foster students' self-regulated learning. *Technology, Instruction, Cognition and Learning, 3*(2), 97-104.

Azevedo, R., Green, J. A., & Moos, D. C. (2007). The effect of human agent's external regulation upon college students' hypermedia learning. Metacognition and Learning. Metacognition and Learning, 2(2-3), 67-87. doi:1007/s11409-007-9014-9

Azevedo, R., Moos, D., Greene, J., Winters, F., & Cromley, J. (2008).Why is externally-facilitated regulated learning more effective than self-regulated learning with hypermedia? *Educational Technology Research & Development, 56*(1), 45-72. doi:10.1007/*s*11423-007-9067-0

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

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

Bembenutty, H. (2008). The last word: An interview with Barry J. Zimmerman: Achieving self-fulfilling cycles of academic self-regulation. *Journal of Advanced Academics, 20,* 174–193. doi:10.4219/jaa-2008-885

Bembenutty, H. (2009). Three essential components of college teaching: achievement calibration, self-efficacy, and self-regulation. *College Student Journal*, *43*(2), 562-570.

Bothma, F., & Monteith, J. L.dK. (2004). Self-regulated learning as a prerequisite for successful distance learning. *South African Journal of Education, 24*(2), 141-147.

Chen, P., & Zimmerman, B. J. (2007). A Cross-National Comparison Study on the Accuracy of Self-Efficacy Beliefs of Middle-School Mathematics Students. *Journal of Experimental Education*, *75*(3), 221-244.

Clarebout, G., &Elen, J. (2006). Tool use in computer-based learning environments: towards a research framework. *Computers in Human Behavior, 22*, 389-411. doi:10.1016/j.chb.2004.09.007

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*, 185-206.

Cleary, T. J., Zimmerman, B. J., & Keating, T. (2006). Training physical education students to self-regulate during basketballfree-throw practice. *Research Quarterly for Exercise and Sport, 77*, 251 – 262.

Cohen, J. (1992). A power primer. *Psychological Bulletin, 112*(1), 155-159.

Dabbagh, N., & Kitsantas, A. (2005). Using web-based pedagogical tools as scaffolds for self-regulated learning. *Instructional Science, 33*(5), 513–540. doi:10.1007/s11251-005-1278-3

Eagleton, M. B., & Dobler, E. (2007). *Reading the web: Strategies for Internet inquiry*. New York, NY: The Guildford Press.

Eagleton, M. B., & Guinee, K. (2002). Strategies for supporting student Internet inquiry. *New England Reading Association Journal, 38*(2), 39-47.

Google (2009). Our search: Google technology. Retrieved from: http://www.google.com/technology/

Graesser, A. C., McNamara, D. S., & VanLehn, K. (2005). Scaffolding deep comprehension strategies through Point&Query, AutoTutor, and iSTART. *Educational Psychologist, 40*(4), 225-234. doi:10.1207/s15326985ep4004_4

Greene, J. A., & Azevedo, R. (2007). Adolescents' use of self-regulatory processes and their relation to qualitative mental model shifts while using hypermedia. *Journal of Educational Computing Research, 36*, 125–148.

Greene, J. A., Moos, D. C., Azevedo, R., & Winters, F. I. (2008). Exploring differences between gifted and grade-level students' use of self-regulatory learning processes with hypermedia. *Computers and Education, 50*, 1069–1083. doi:10.1016/j.compedu.2006.10.004

Hadwin, A. F., Nesbit, J. C, Jamieson-Noel, D., & Code, J., & Winne, P. H. (2007). Examining trace data to explore self-regulated learning. *Metacognition Learning, 2*(2-3). 107-124. doi:10.1007/s11409-007-9016-7

Hannafin, M., Land, S., & Oliver, K. (1999). Open learning environments: foundation, methods, and models. In C. M. Reigeluth (Ed.), Instructional-design theories and models: A new paradigm of instructional theory, Vol. II (pp. 115–140). Mahwah, NJ, US: Lawrence Erlbaum.

Hattie, J. &Timperley, H. (2007). The Power of Feedback. *Review of Educational Research, 77*(1), 81-112. doi:10.3102/003465430298487

Ikpeze, C.H., & Boyd, F.B. (2007). Web-based inquiry learning: Facilitating thoughtful literacy with WebQuests. *The Reading Teacher, 60*(7), 644–654. doi:10.1598/RT.60.7.5

Kauffman, D. F. (2004). Self-regulated learning in web-based environments: instructional tools designed to facilitate cognitive strategy use, metacognitive processing, and motivational beliefs. *Journal of Educational Computing Research, 30*(1&2), 139–161.

Kauffman, D. F., Ge, X., Xie, K., & Chen, C. (2008). Prompting in web-based environments: Supporting self-monitoring and problem solving skills in college students. Journal of Educational Computing Research, 38(2), 115-137. doi: 10.2190/EC.38.2a

Kitsantas, A., & Dabbagh, N. (2004). Promoting self-regulation in distributed learning environments with web-based pedagogical tools: An exploratory study. Journal of Excellence in College Teaching, 15(1–2), 119–142.

Kitsantas, A. & Dabbagh, N. (2010). Learning to Learn with Integrative Learning Technologies (ILT): A Practical Guide for Academic Success. Information Age Publishing.

Kitsantas, A., & Zimmerman, B. J. (2002). Comparing self-regulatory processes among novice, non-expert, and expert volleyball players: a microanalytic study. *Journal of Applied Sport Psychology, 14*, 91-105. doi:10.1080/10413200252907761

Lim, B. (2004). Challenges and issues in displaying inquiry on the web*. British Journal of Educational Psychology, 35*(5), 627-643. doi:10.1111/j.0007-1013.2004.00419.x

Linn, M. C., &Eylon, B. (2006). Science education: Integrating views of learning and instruction. In P. Alexander & P. Winne (Eds.), *Handbook of Educational Psychology* (2nd ed.). Mahwah, NJ: Lawrence Erlbaum Associates, Inc.

Lajoie, S., & Azevedo, R. (2006). Teaching and learning in technology-rich environments. In P. Alexander & P. Winne (Eds.), *Handbook of Educational Psychology* (2nd ed.). Mahwah, NJ: Lawrence Erlbaum Associates, Inc.

Manlove, S, Lazonder, A. W., & Jong, T. (2007). Software scaffolds to promote regulation during scientific inquiry learning. *Metacognition Learning, 2*(2-3). 141-155. doi:10.1007/s11409-007-9012-y

Mayer, R. E. (2003). Learning environments: The case for evidence-based practice and issue-driven research. *Educational Psychology Review, 15*(4), 359-373.

Mitchell, T. R., Hopper, H., & Daniels, D. (1994). Predicting self-efficacy and performance during skill acquisition. *Journal of Applied Psychology, 79*(4), 506-517.

Moos, D. C., & Azevedo, R. (2006). The role of goal structure in undergraduates' use of self-regulatory processes in two hypermedia learning tasks. *Journal of Educational Multimedia and Hypermedia, 15*(2), 49–86.

Moos, D. C., & Azevedo, R. (2008). Monitoring, planning, and self-efficacy during learning with hypermedia: the impact of conceptual scaffolds. *Computers in Human Behavior, 24*(4), 1686–1706. doi:10.1016/j.chb.2007.07.001

Moos, D. C., & Azevedo, R. (2009a). Self-efficacy and prior domain knowledge: to what extent does monitoring mediate their relationship with hypermedia learning? *Metacognition and Learning, 4*(1). 87-95. doi:10.1007/s11409-009-9045-5

Moos, D.C., & Azevedo, R. (2009b). Learning with computer-based learning environments: A literature review of computer self-efficacy. *Review of Educational Research. 72*(2), 576-600. doi:10.3102/00345654308326083

National Research Council (2000). Inquiry and the National Science Education Standards: A guide for teaching and learning. Washington, DC: National Academy Press. Retrieved from: http://www.nap.edu/catalog.php?record_id=9596

Nenniger, P. (2006). Comment on Perry &Winne's "learning from learning kits: gStudy traces of students' self-regulated engagements with computerized content". *Educational Psychology Review, 18*, 233-237. doi:10.1007/s10648-006-9015-2

Nesbit, J. C., Winne, P. H., Jamieson-Noel, D., Code, J., Zhou, M., MacAllister, K., et al. (2006). Using cognitive tools in gStudy to investigate how study activities covary with achievement goals. *Journal of Educational Computing Research, 35*(4), 339–358.

Nolen, S. B. (2006). Validity in assessing self-regulated learning: A comment on Perry & Winne. *Educational Psychology Review, 18*, 229-232. doi:10.1007/s10648-006-9016-1

Pajares, F. (1996). Self-efficacy beliefs and mathematical problem-solving of gifted students. *Contemporary Educational Psychology, 21*, 325-344.

Pajares, F. & Graham, L. (1999). Self-efficacy, motivation constructs, and mathematics performance of entering middle school students. *Contemporary Educational Psychology, 24*, 214–139.

Perry, N. E., & Winne, P. H. (2006). Learning from learning kits: gStudy traces of students' self-regulated engagements with computerized content. *Educational Psychology Review, 18*, 211-228. doi:10.1007/s10648-006-9014-3

Pieschl, S. (2009). Metacognitive calibration-an extended conceptualization and potential applications. *Metacognition Learning, 4*, 3-31. doi:10.1007/s11409-008-9030-4

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

Pintrich, P., Smith, D.F., Garcia, T., & McKeachie, W.J. (1991). The manual for the use of the Motivated Strategies for Learning Questionnaire (MSLQ) (Tech. Rep. No. 91-B-004). Ann Arbor: University of Michigan, School of Education.

Proske, A., Narciss, S., & Korndle, H. (2007). Interactivity and learners' achievement in web-based learning. *Journal of Interactive Learning Research, 18*(4), 511–531.

Quintana, C., Zhang, M., & Krajcik, J. (2005).A framework for supporting metacognitive aspects of online inquiry through software-based scaffolding. *Educational Psychologist, 40*(4), 235-244. doi:10.1207/s15326985ep4004_5

Rogers, D., & Swan, K. (2004). Self-regulated learning and internet searching. *Teachers College Record, 106*(9), 1804-1824. doi:10.1111/j.1467-9620.2004.00406.x

Salvoraara, H. (2005). An exploration of students' strategy use in inquiry based computer supported collaborative learning. *Journal of Computer Assisted Learning, 21*(1), 39-52. doi:10.1111/j.1365-2729.2005.00112.x

Schraw, G. (2007). The use of computer-based environments for understanding and improving self-regulation. *Metacognition Learning, 2*, 169-176. doi:10.1007/s11409-007-9015-8

Schunk D. H. (1995). Self-efficacy and education and instruction. In J. E. Maddux (Ed.), *Self-efficacy, adaptation, and adjustment: Theory, research, and application* (pp. 281-303). New York: Plenum.

Schunk, D. H., & Ertmer, P. A. (1999). Self-regulatory processes during computer skill acquisition: goal and self-evaluative influences. *Journal of Educational Psychology, 91*(2), 251–260.

Schraw, G. (1995). Measures of feeling-of-knowing accuracy: A new look at an old problem. *Applied Cognitive Psychology, 9*, 321–332. doi:10.1002/acp.2350090405.

Spitzer, R. L., Cohen, J., Fleiss, J. & Endicott, J. (1973). Quantification of agreement in psychiatric diagnosis, *Archives of General Psychiatry, 17*, 83-87.

Stone, N. J. (2000). Exploring the relationship between calibration and self-regulated learning. *Educational Psychology Review, 12*(4), 437–475. doi:10.1023/A:1009084430926.

The College Board (2010). Essay Scoring Guide: A framework for scoring SAT essays. Retrieved from: http://professionals.collegeboard.com/testing/sat-reasoning/scores/essay/guide

Thompson, L. F., Meriac, J. P. & Cope, J. G. (2002). Motivating online performance: The influences of goal setting and Internet self-efficacy. *Social Science Computer Review, 20*, 149-160.

Tsai, C. (2004). Beyond cognitive and metacognitive tools: the use of the internet as an 'epistemological' tool for instruction. *British Journal of Educational Technology, 35*(5). 525-536. doi: 10.1111/j.0007-1013.2004.00411.x

Tsai, M. (2009). Online information searching strategy inventory (OISSI): A quick version and a complete version. Computers and Education, 53, 473-483. doi:10.1016/j.compedu.2009.03.006

White, B., &Frederiksen, J. (2005). A theoretical framework and approach for fostering metacognitive development. *Educational Psychologist, 40*(4), 211-223. doi:10.1207/s15326985ep4004_3

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* (2nd ed., pp. 153–189). Mahwah, NJ: Lawrence Erlbaum.

Winne, P. H. (2006). How software technologies can improve research on learning and bolster school reform. *Educational Psychologist, 41*, 5-17. doi:10.1207/s15326985ep4101_3

Winne, P. H., & Hadwin, A. F. (1998). Studying as self-regulated learning. In D. J. Hacker, J. Dunlosky, & A. Graesser (Eds.), *Metacognition in educational theory and practice* (pp. 277–304). Hillsdale, NJ: Lawrence Erlbaum.

Winne, P. H., & Jamieson-Noel, D. L. (2002). Exploring students' calibration of self-reports about study tactics and achievement. *Contemporary Educational Psychology, 27*, 551–572. doi:10.1016/S0361-476X(02)00006-1

Winne, P. H., Nesbit, J. C., Kumar, V., Hadwin, A. F., Lajoie, S. P., Azevedo, R. A., & Perry, N. E. (2006). Supporting self-regulated learning with gStudy software: The Learning Kit Project. *Technology, Instruction, Cognition and Learning, 3*(1), 105-113.

Winters, F. I., Green, J. A., &Costich, C. M. (2008). Self-regulation of learning with computer-based learning environments: A critical Analysis. *Educational Psychology Review, 20*, 429-444. doi:10.1007/s10648-008-9080-9

Zimmerman, B. J. (1998). Academic studying and the development of personal skill: A self-regulatory perspective. *Educational Psychologist, 33*(2/3), 73-86.

Zimmerman, B. J. (2000). 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: Academic Press.

Zimmerman, B. J. (2001). Theories of Self-regulated learning and academic achievement: An overview and analysis. In B. J. Zimmerman & D. H. Schunk (Eds.), *Self-regulated learning and academic achievement: Theoretical perspectives* (2nd ed., pp. 1–37). Mahwah, NJ: Lawrence Erlbaum.

Zimmerman, B. J. (2002). Becoming a self-regulated learner: An overview. *Theory into practice, 41*, 64-70.

Zimmerman, B. J. (2008a). Goal setting: A key proactive source of academic self-regulation. In D. H. Schunk & B. J. Zimmerman (Eds.), *Motivation and self-regulated learning: Theory, research, and applications* (pp. 267–296). New York, NY: Lawrence Erlbaum.

Zimmerman, B. J. (2008b). Investigating Self-Regulation and Motivation: Historical Background, Methodological Developments, and Future Prospects. *American Educational Research Journal, 45*(1), 166-183. doi:10.3102/0002831207312909

Zimmerman, B. J., & Kitsantas, A. (2002). Comparing self-regulatory processes among novice, non-expert, and expert volleyball players: a microanalytic study. *Journal of Applied Sport Psychology, 14*, 91-105. doi:10.1080/10413200252907761

Zimmerman, B. J., & Kitsantas, A. (2005). Acquiring writing revision and self-regulatory skill through observation and emulation. *Journal of Educational Psychology, 94*(4), 660-668. doi:10.1037//0022-0663.94.4.660

Zimmerman, B. J., & Tsikalas K. E. (2005). Can computer-based learning environments (CBLEs) be used as self-regulatory tools to enhance learning? *Educational Psychologist, 40*(4), 267-271. doi:10.1207/s15326985ep4004_8