

ASSOCIATIONS BETWEEN SELF-EFFICACY BELIEFS, SELF-REGULATED
LEARNING STRATEGIES, AND STUDENTS' PERFORMANCE ON MODEL-
ELICITING TASKS: AN EXAMINATION OF DIRECT AND INDIRECT EFFECTS

By

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To my late sister, Shivani Sharda

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LIST OF ABBREVIATIONS

ANOVA	Analysis of Variance
CCMS	Connected Classroom in Promoting Mathematics
CCSSM	Common Core State Standards for Mathematics
CCSSO	Council of Chief State School Officers
CFA	Confirmatory Factor Analysis
MAR	Missing at Random
MCAR	Missing Completely at Random
MEAs	Model-Eliciting Activities
MI	Modification Indices
ML	Maximum Likelihood
MSLQ	Motivated Strategies for Learning Questionnaire
OECD	Organization for Economic Cooperation and Development
PISA	Programme for International Student Assessment
RMSEA	Root Mean Square Error of Approximation
SEM	Structural Equation Modeling
SPSS	Statistical Package for the Social Sciences
SRL	Self-Regulated Learning
TIMSS	Trends in Mathematics and Science Study
TLI	Tucker Lewis Index
WLSMV	Weighted Least Square Means and Variance Adjusted

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Mathematics education currently emphasizes engaging students in mathematical modeling to understand problems of everyday life and society (Council of Chief State School Officers (CCSSO), 2010; English & Sriraman, 2010; Lesh & Zawojewski, 2007). The Common Core State Standards for mathematics also stress that high school students should develop understanding of algebra, functions, statistics, and geometry in conjunction with modeling (CCSSO, 2010). A review of mathematical modeling literature indicated a lack of information regarding which contextual factors impact students' success in solving modeling activities. The present study attempts to fill this gap by examining associations between self-efficacy beliefs, self-regulated learning strategies (e.g., cognitive and metacognitive strategy use), and students' performance in modeling tasks.

Self-efficacy beliefs were measured by developing a new instrument, Modeling Self-Efficacy scale. Data for participants' self-reported use of cognitive and metacognitive strategies were gathered through their responses on the modified version of the Motivated Strategies for Learning Questionnaire (Kaya, 2007). Modeling

outcomes were measured in terms of students' success in solving six modeling problems. These problems were adapted from the PISA 2003 problem-solving assessment.

The confirmatory factor analysis indicated an acceptable fit of the data with the hypothesized measurement model. The structural model tested using Structural Equation Modeling techniques suggested that perceived modeling self-efficacy beliefs ($\beta = .50, p < .001$) directly and positively predicted students' performance in solving modeling problems. However, organization strategy use ($\beta = -.62, p < .05$) had a significant negative direct effect on students' modeling success. The direct effects of students' use of critical thinking ($\beta = -.59, p = .08$), elaboration ($\beta = .40, p = .41$), and metacognitive strategies ($\beta = .46, p = .16$) on their performance in solving modeling tasks were non-significant. Also, indirect effects of students' self-efficacy beliefs on modeling task success through their effect on their use of cognitive and metacognitive strategies were non-significant. The implications for future research along with limitations of this study are discussed.

CHAPTER 1 INTRODUCTION

One of the core tenets of Common Core State Standards for Mathematics (CCSSM) is to prepare students for the 21st century global society (Council of Chief State School Officers (CCSSO), 2010). Towards this end, the Standards for Mathematical Practice specify that students should solve real-world problems by engaging in modeling activities. Modeling with mathematics is the process of using knowledge and skills from across and within the curriculum to solve problems arising in everyday life, society, and workforce (CCSSO, 2010). Mathematical modeling is not only an important mathematical practice that teachers should promote through classroom instruction, discussions, and activities but also a conceptual category in high school standards where it is expected that students should learn algebra, functions, probability, and statistics in conjunction with modeling (CCSSO, 2010). The authors state that,

Modeling links classroom mathematics and statistics to everyday life, work, and decision-making. It is the process of choosing and using appropriate mathematics and statistics to analyze empirical situations, to understand them better, and to improve decisions. Quantities and their relationships in physical, economic, public policy, social, and everyday situations can be modeled using mathematical and statistical methods (CCSSO, 2010, p. 72).

The importance of and need to prepare students for a global society and workforce is further emphasized through statistics that show that U.S. students rank significantly below European and Asian students on international assessments such as PISA (Programme for International Student Assessment) and TIMSS (Trends in Mathematics and Science Study). PISA 2003 tested the problem-solving skills of 15-year-old students by examining their readiness to meet the challenges of today's global and technological society. Specifically, it measured the extent to which students across

the world can solve real-life situations by thinking flexibly and creatively. Sadly, American students ranked 25th among peers from 38 participating Organization for Economic Cooperation and Development (OECD) countries (Lemke et al., 2004). The U.S. average score on the problem-solving scale was also lower than the average OECD score. TIMSS 2007, on the other hand, measured eighth-grade students' mastery of curriculum-based mathematical knowledge and skills. Although U.S. students' mean mathematics score was above the TIMSS average score and their performance was better than previous assessment years, only six percent of American students were able to "organize information, make generalizations, solve non-routine problems, and draw and justify solutions from data" (Gonzales et al., 2009, p. 14).

These results point toward the need to improve U.S. students' problem-solving behaviors, especially in regard to solving problems in real life. One way to do this is by developing students' expertise in modeling practices. Since modeling as a Standard for Mathematical Practice puts forth the expectation that students should develop expertise in solving real-world situations (CCSSO, 2010), the present study is interested in investigating factors that may influence students' modeling outcomes. Due to a lack of literature informing which contextual factors impact students' success in solving real-world modeling tasks, the present study draws upon problem-solving literature to explore the degree to which effective problem-solving behaviors are associated with students' modeling outcomes.

Effective problem-solving behaviors, such as setting appropriate goals, controlling one's actions, monitoring one's progress, reflecting back on one's thinking, trying alternative solution paths, and perseverance with challenging academic tasks,

align very closely with the self-regulated learning (SRL) behaviors (Pape & Smith, 2002; DeCorte, Verschaffel, & Op't Eynde, 2000; Zimmerman & Campillo, 2003). Self-regulated students control and regulate their thoughts, actions, behaviors, and motivation in order to achieve a targeted goal (Schunk & Zimmerman, 1994; Zimmerman, 2000). They use effective learning strategies, constantly monitor and assess their progress toward their goal, reflect on their thought processes, expend more effort, persist longer, stay motivated on the task, and create productive learning environments (Schunk & Zimmerman, 2008; Zimmerman, 2000). SRL strategies not only enhance students' academic performance (Dignath, Buettner, & Langfeldt, 2008; Zimmerman, 2002; Zimmerman & Kitsantas, 2005) but also increase their motivation to learn (Pintrich, 1999).

Out of numerous behaviors, attitudes, and beliefs exercised by self-regulated learners, motivational beliefs such as self-efficacy judgments and SRL strategies such as cognitive and metacognitive strategy use profoundly influence students' engagement and persistence on complex mathematical tasks and their academic performance (De Corte et al., 2000; Hoffman & Spataru, 2008; Pape & Wang, 2003; Puteh & Ibrahim, 2010; Verschaffel et al., 1999). Several studies have reported that self-efficacy beliefs are related to and predictive of students' problem-solving performance (Greene, Miller, Crowson, Duke, & Alley, 2004; Pajares, 1996; Pajares & Graham, 1999; Pajares & Kranzler, 1995; Pajares & Miller, 1994; Pajares & Valiante, 2001; Pintrich & DeGroot, 1990). Students' judgments of their problem-solving performance positively impact their engagement, behavior, and cognition during academic activities. Further, students' perceived capabilities to use a variety of cognitive and metacognitive strategies also

influence their academic achievement (Pape & Wang, 2003; Pintrich & De Groot, 1990; Pintrich, Smith, Garcia, & McKeachie, 1993; Zimmerman & Martinez-Pons, 1986, 1988, 1990). Cognitive and metacognitive strategies not only help problem solvers in planning, monitoring, evaluating, and revising courses of actions, but also encourage them to be more flexible in selecting a solution plan or a strategy. Research also shows that students with high academic self-efficacy beliefs are more likely to report using cognitive and metacognitive strategies and they persist longer to reach their goals (Bouffard-Bouchard, Parent, & Larivee, 1991; Heidari, Izadi, & Ahmadian, 2012; Nevill, 2008; Pintrich & DeGroot, 1990).

The present study built upon and extended existing problem-solving literature by examining these associations in the context of mathematical modeling and real-life problem solving. Specifically, the present study explored associations between motivational beliefs (e.g., self-efficacy beliefs), SRL strategies (e.g., cognitive and metacognitive strategies), and modeling outcomes. The next section describes the background of the study including the average performance of students on international assessments to illustrate that modeling problems are not only difficult for U.S. students but also challenging for students all over the world. This is followed by a brief overview of mathematical modeling and SRL processes. The chapter concludes with a statement of the problem, purpose of the study, research questions, and significance of the study.

Background of the Study

Today's global society and changing economy require students to be creative thinkers and effective problem solvers. This is because the kind of mathematical thinking that is needed beyond school has changed significantly with the advent of new communication and collaboration technologies (English, Lesh, & Fennewald, 2008;

Lesh, 2000). For example, the actual price of a car is much more than the sticker price. Determining the actual cost of a vehicle involves interpreting loans, down payment, monthly payments, annual percentage rate, and billing periods. Yet, most classrooms are still not preparing students for life beyond school as they seldom provide students with opportunities to apply what they have been learning to understand problems situated in real-world contexts (English et al., 2008).

The average performance of students from all over the world on international assessments (e.g., PISA, TIMSS) further shows their lack of experience in relation to real-life problem solving. PISA 2003 tested students' real-life problem-solving skills by measuring the extent to which they can successfully solve "cross-disciplinary situations where the solution path is not immediately obvious and where the content areas or curricular areas that might be applicable are not within a single subject area of mathematics, science or reading" (OECD, 2004, p. 26). Students' problem-solving abilities were measured through three different types of problems including decision-making, system analysis and design, and troubleshooting (OECD, 2004). These problems were carefully selected to encompass several problem-solving abilities that students may need in understanding day-to-day situations. Some of the problem-solving abilities tested by PISA include making appropriate decisions, choosing strategically among several alternatives, analyzing situations, describing underlying relationships, designing systems, or diagnosing and rectifying faulty systems.

In all, 38 countries participated in the PISA 2003 problem-solving assessment. PISA rated students' performance on a problem-solving scale for which the mean score was 500 points. Sadly, the overall problem-solving score of only 17 of the 38

participating countries was higher than the OECD average score of 500. The PISA problem-solving scale also distinguishes students' abilities across three proficiency levels. Level three represents students with the strongest problem-solving skills, and level one denotes students with the weakest problem-solving skills. The percentage distribution of 15-year-old students on the problem-solving scale indicated that 17 percent of the students that participated in the PISA problem-solving assessment scored below level one, 30 percent at level one, 34 percent at level two, and 18 percent at level three (Lemke et al., 2004). There were only four countries (e.g., Finland, China, Japan, and Korea) that had 30 percent or more of their students scoring at level three.

In contrast to PISA, TIMSS 2007 measured eighth-grade students' school-based mathematical knowledge and skills (Gonzales et al., 2008). Students' mathematics achievement was measured by testing their subject matter knowledge in the area of number sense, algebra, geometry, and data and chance. Students' cognitive skills were assessed in three domains including knowledge of mathematical facts, procedures, and concepts (knowing), ability to apply known operations, methods, and strategies (applying), and ability to handle unfamiliar situations, complex contexts, and multi-step problems (reasoning).

TIMSS measured students' performance on a scale ranging from 0 to 1000 with an average score of 500 (Gonzales et al., 2008). Of the 48 participating countries, the mathematics score of only 12 countries was higher than the TIMSS average score. There were 18 countries that scored higher than 500 points in the areas of knowing, applying, and reasoning. Further, participating students' performance against international benchmarks of mathematics achievement showed that there were only five

countries who had a significant percentage of 8th-grade students (e.g., 26% to 45%) reaching the advanced level skills including organizing information, making generalizations, solving non-routine problems, drawing conclusions, and justifying solutions (Mullis, Martin, & Foy, 2008). The rest of the 43 countries had fewer than 10 percent of their students demonstrating advanced level skills.

Thus, both PISA and TIMSS assessments point toward the need to improve students' problem-solving behaviors, especially in regard to solving problems in real life. Learning mathematics with modeling has been cited as one of the possible solutions because modeling not only improves transfer but also fosters 21st century skills of reasoning, critical thinking, and strategic decision-making (English, 2011; English & Sriraman, 2010; Lesh & Zawojewski, 2007).

Mathematical Modeling

According to a models and modeling perspective, students understand real-world situations by participating in iterative cycles of modeling where they progressively create, test, revise, and refine their mathematical interpretations (Lesh & Harel, 2003). Such interpretations are largely influenced by students' existing knowledge and experiences as well as beliefs and attitudes that they bring to the classroom (Eric, 2010). In the field of mathematical modeling, students' purposeful descriptions, interpretations, and explanations of mathematical situations are known as models. Examples of mathematical models include equations, graphs, tables, written symbols, spoken language, diagrams, metaphors, concrete models, or computer-based simulations (Lesh, Hoover, Hole, Kelly, & Post, 2000; Lesh & Doerr, 2003). Further, mathematical tasks that require students to understand real-life situations through developing models are known as model-eliciting activities (MEAs) or modeling tasks

(Lesh et al., 2000). Students develop efficient models for these activities by engaging in several modeling cycles (Mousoulides, Christou, & Sriraman, 2008; Lesh & Doerr, 2003; Lesh & Zawojewski, 2007). Each modeling cycle consists of four different modeling processes including (1) understanding the modeling task (description), (2) developing a mathematical model (manipulation), (3) interpreting the actual situation based on the created model (prediction), and (4) analyzing and reflecting upon the results (verification). Furthermore, it is important to note that this modeling cycle bears some structural similarity to many of the general problem-solving heuristics proposed over the years by researchers such as Polya (1957), Newell and Simon (1972), and Bransford and Stein (1984).

Polya's four steps to solving a problem include understanding the problem, devising a plan, carrying out the plan, and looking back. Although the process of describing a modeling task and understanding a problem-solving task involve making sense of the task, the cognitive skills required to comprehend modeling tasks are more demanding. Problem-solving strategies such as representing the problem, separating various parts of a problem, organizing data in the form of a table, or making connections between the known and unknown information may help students in understanding a word problem. In addition to these strategies, modeling tasks challenge students' competency to mathematize realistic situations, which includes "sorting, organizing, selecting, quantifying, weighting, and transforming large data sets" (English & Sriraman, 2010, p. 273).

The second step in Polya's heuristic requires students to devise a solution plan for a mathematical problem by looking for a problem having the same or similar

unknowns, employing strategies or methods of previously solved problems, looking for patterns, making an orderly list, considering special cases, or solving the same problem by making use of smaller numbers. On the other hand, during the manipulation phase of the modeling cycle students generate hypotheses about a given situation by developing a mathematical model that represents relationships between different variables involved in a system. However, it may also include modifying a previously developed model.

During Polya's next stage, carrying out the plan, students implement the steps required to solve a problem as well as make sure that each step is mathematically correct. Model development processes, however, place less emphasis on the precision and accuracy of the solutions and stress the importance of correctly predicting the actual situation based on the model created (e.g., making decisions, designing systems, or diagnosing faulty systems).

Verification processes involved in Polya's heuristic and the model development cycle encourage students to analyze and look back on their solutions, especially to judge the accuracy of their solutions or models. It is important to note, however, that verification processes involved during model development clearly emphasize the need to re-understand and re-interpret the situation when the created model fails to explain the real-world situation. Research also shows that students interpreting modeling activities seldom produce effective models during their engagement with the first cycle of modeling processes (English, 2006; Eric, 2010; Mousoulides, Pittalis, Christou, & Sriraman, 2010). The following section describes the cognitive and metacognitive processes involved in solving problems as well as motivational beliefs exhibited by effective problem solvers, which align very closely with SRL processes.

Self-Regulatory Processes and Problem Solving

Social cognitive theory is a useful framework for understanding SRL behaviors that enhance students' problem-solving skills (Zimmerman & Campillo, 2003). The theory describes human functioning in terms of reciprocal interactions between personal variables, environmental factors, and behavioral objectives (Bandura, 1986). It presents a view of human agency where people make meaningful and purposeful choices to achieve goals. For example, students' personal beliefs such as self-efficacy beliefs influence their learning behaviors such as choice of problem-solving strategies, effort expended, and persistence (Pintrich & De Groot, 1990; Schunk & Mullen, 2012). In turn, effective use of cognitive and metacognitive strategies raises students' confidence about their problem-solving capabilities, which motivates them to work harder to produce meaningful solutions. The triadic reciprocal interaction also influences the three cyclical phases of self-regulation: forethought, performance, and self-reflection.

During the forethought phase, problem-solvers analyze the requirements of a task, establish achievable goals, and design solution plans by selecting strategies appropriate to achieve these goals (Zimmerman, 2000). These processes are influenced by several motivational beliefs such as self-efficacy beliefs, outcome expectations, intrinsic interest, and goal orientation. Out of these, self-efficacy beliefs involving students' perceptions of their own capabilities to accomplish a particular task have been extensively explored in the context of mathematical problem solving (Hoffman & Spatariu, 2008; Pajares, 1996; Pajares & Graham, 1999; Pajares & Miller, 1994; Schunk & Pajares, 2009; Schunk & Mullen, 2012). Self-efficacious problem solvers set challenging goals, expend more effort, use effective learning strategies, and persist longer in times of difficulties (Pajares, 2008; Schunk & Pajares, 2009).

The next phase, performance phase, comes into play when students are actually engaged in solving mathematics problems or preparing for a test. Effective problem solvers increase their attention and persistence over tasks through self-instruction, attention focusing, and task strategies. They also utilize self-observation processes, such as self-monitoring and self-recording, to monitor their progress toward the goals as well as to check their understanding of the task (Dabbagh & Kitsantas, 2004). From the problem-solving perspective, these are important SRL strategies because they support students in finding errors in their learning and prompt them to adjust their strategies and procedures in case they are not making adequate progress. Error analyses are closely followed by self-evaluation and self-reaction processes of the self-reflection phase (Cleary & Zimmerman, 2012). Self-regulated learners self-evaluate their performance against their personal goals and attribute their mistakes to a lack of adequate effort (Zimmerman, 2000; Zimmerman & Campillo, 2003). Effective and ineffective problem solvers have been found to behave and react differently in all three phases of self-regulation (Clearly & Zimmerman, 2001; Zimmerman & Campillo, 2003).

Although there are numerous motivational beliefs and SRL behaviors that support students during problem solving, the present study emphasized the importance of self-efficacy beliefs and SRL strategies such as cognitive and metacognitive strategies. Cognitive strategies support students in processing information, such as elaboration, organization, and critical thinking. Elaboration strategies, such as paraphrasing, summarizing, and note taking, facilitate students in developing meaningful representations (or models) for the problems. The organization strategies, such as clustering, outlining, and selecting main ideas, are helpful in differentiating

relevant and irrelevant information. These strategies may be useful in solving system analysis and design problems, where students represent relationships among different parts of a system either in the form of a table or a chart. Finally, critical thinking strategies support students to make logical decisions and analysis. These strategies are considered to be the most important skills as they help students to think logically, consider alternative conceptions of a problem, make effective decisions, reason deductively as well as justify reasoning (Stein, Haynes, Redding, Ennis, & Cecil, 2007).

Metacognitive strategies including monitoring, controlling, and regulating cognition and learning support students in self-evaluating the effectiveness of their models, creating revised models, group decision making, and describing situations using models. These processes are especially important during students' engagement with the successive modeling cycles of describing, manipulating, predicting, and verifying situations using models. The present study examined associations between self-efficacy beliefs, self-reported use of cognitive strategies (e.g., elaboration, organization, and critical thinking) and metacognitive strategies (e.g., planning, monitoring, and regulating), and students' modeling outcomes.

Statement of the Problem

Mathematics education currently emphasizes providing students with opportunities to apply mathematical knowledge and skills to understand problems of everyday life and society (CCSSO, 2010; English & Sriraman, 2010; Lesh & Zawojewski, 2007). The CCSSM also emphasize that high school students should develop understanding of algebra, functions, statistics, and geometry within real-world contexts. In spite of this, the current mathematics textbooks, teaching practices, and assessment techniques hardly support students in developing understandings and

abilities useful for mathematical modeling (Lesh, 2003). The adoption of CCSSM, however, offers some hope regarding preparing students with skills useful for life beyond school. The Standards for Mathematical Practice describe the kind of mathematical knowledge and skills to be fostered in classrooms with regard to modeling. As such, they do not inform teachers about factors that may influence students' achievement on modeling tasks. To this end, the literature on models and modeling perspective is also of little help because it is still developing. Kaiser, Blomhøj, and Sriraman (2006) argued, "The theory of teaching and learning mathematical modeling is far from being complete. Much more research is needed, especially in order to enhance our understanding on micro levels, meaning teaching and learning problems, which occur in particular educational settings where students are engaged in modeling activities" (p. 82). The present study attempts to fill this gap by examining associations between effective problem-solving behaviors and student success rates on modeling tasks.

Purpose of the Study

The present study is aimed toward investigating factors that may influence students' ability to apply mathematical knowledge in understanding modeling tasks or real-world situations. Problem-solving literature informs us that self-efficacy beliefs (Greene et al., 2004; Pajares & Graham, 1999; Pajares & Krazler, 1995; Pajares & Miller, 1994) and SRL strategy use (Zimmerman & Martinez-Pons, 1986, 1988, 1990) significantly correlate with students' performance on complex mathematical tasks. Thus, the focus of this research is to examine relationships between self-efficacy beliefs, cognitive and metacognitive strategy use, and students' success on modeling tasks. Modeling processes including building, describing, testing, revising, manipulating, and

verifying models align very closely with the three types of problem-solving tasks (e.g., decision-making, system analysis and design, and troubleshooting tasks) chosen by the PISA 2003 assessment (Blum, 2011; Mousoulides, 2007). The present study, therefore, examined associations between self-efficacy beliefs, cognitive and metacognitive strategy use, and students' ability to correctly solve decision-making, system analysis and design, and troubleshooting tasks.

Research Questions

The study was guided by three research questions.

1. What are the direct effects of students' self-efficacy beliefs for modeling tasks on their performance on modeling tasks?
2. What are the direct effects of students' self-reported use of cognitive and metacognitive strategies on their performance on modeling tasks?
3. What are the indirect effects of students' self-efficacy beliefs for modeling tasks on their performance on modeling tasks through their effects on their use of cognitive and metacognitive strategies?

Significance of the Study

The present study was stimulated by the need for research that examines students' beliefs and skills that may impact their performance on the modeling tasks. A review of the problem-solving literature indicated that motivational beliefs, such as self-efficacy beliefs, and SRL strategies, such as cognitive and metacognitive strategies, are related to students' academic achievement and problem-solving success. Studies that investigated the effects of self-efficacy beliefs reported that students' perceived confidence in their ability is positively correlated with their problem-solving skills and academic performance (Pajares, 1996; Pajares & Graham, 1999; Pajares & Kranzler, 1995; Pajares & Miller, 1994, Pajares & Valiante, 2001; Pintrich, 1999; Pintrich & De Groot, 1990). Students' reported use of cognitive and metacognitive strategies are also

positively associated with their learning and problem-solving performance (Pape & Wang, 2003; Verschaffel et al., 1999; Zimmerman & Martinez-Pons, 1986, 1988, 1990). The present study extends our understanding of how students' beliefs about their capabilities as well as use of cognitive and metacognitive strategies are associated with their modeling task success. Thus, the results of this study provide researchers and educators with information on factors that may enhance students' success in modeling tasks.

Furthermore, the present study developed a new instrument, the Modeling Self-Efficacy scale, to measure students' perceptions of modeling competence. The psychometric properties of this scale including internal consistency and construct validity were tested using this sample. As such, development of this new scale contributes to the literature related to self-efficacy theory and the mathematical modeling field.

Definition of Terms

- **COGNITIVE STRATEGIES.** Learning strategies that influence students' processing of information (Pintrich et al., 1993). The present study highlights the importance of three cognitive strategies such as elaboration, organization, and critical thinking.
- **CRITICAL THINKING STRATEGIES.** These strategies support students in logical decision-making especially in considering alternative conceptions of a problem, making effective decisions, reasoning deductively, and justifying reasoning.
- **DECISION-MAKING TASKS.** These are real-world problems requiring students to make appropriate decisions by choosing strategically among several alternatives provided under a given set of conditions (OECD, 2004).
- **ELABORATION STRATEGIES.** Strategies that help students to understand challenging modeling situations by making connections with their existing mathematical knowledge and skills (Ormord, 2008). Examples include paraphrasing, summarizing, creating analogies, and explaining ideas to others.

- **MATHEMATICAL MODELING.** It is the process of using knowledge and skills from across and within the curriculum to solve problems arising in everyday life, society, and workforce (CCSSO, 2010).
- **METACOGNITIVE STRATEGIES.** Metacognitive strategies including planning, monitoring, controlling, and regulating cognition and learning support students in self-evaluating the effectiveness of their models, creating revised models, group decision making, and describing situations using models.
- **MODEL-ELICITING ACTIVITIES.** These are real-world mathematical situations that are generally understood by creating, testing, and revising models (Lesh et al., 2000).
- **MODELING OUTCOMES.** It represents outcomes of engaging students in modeling activities. In this study, modeling outcomes include ability to analyze real-world problems by drawing effectively on multi-disciplinary knowledge, planning, monitoring, and assessing progress, making decisions, troubleshooting faulty systems, or analyzing structures of complex systems.
- **MODELING PROCESSES.** Modeling processes, such as building, describing, manipulating, predicting, testing, verifying, and revising mathematical interpretations, are the cognitive and metacognitive processes employed by students to produce efficient models.
- **MODELS.** Models are conceptual systems that represent how students are thinking, interpreting, and describing modeling tasks (Lesh & Doerr, 2003). Models can be as simple as writing a mathematical equation to depict a relationship between two variables or as complicated as creating a spreadsheet to plan an event.
- **ORGANIZATION STRATEGIES.** Organization strategies, such as clustering, outlining, and selecting main ideas, are helpful in differentiating relevant and irrelevant information. These strategies may be useful in solving system analysis and design problems, where students are expected to organize information in meaningful ways.
- **REAL-LIFE PROBLEMS.** Real-life problems are simulations of the situations actually faced by students in their “personal life, work and leisure, and in the community and society” (OECD, 2004, p. 27). Students generally understand these problems by applying their personal knowledge and prior experiences.
- **SELF-EFFICACY BELIEFS.** It refers to individuals’ perceptions of their own capabilities to accomplish a particular task (Bandura, 1986). In this study, self-efficacy beliefs are defined as students’ judgments of their own abilities to accurately solve decision-making, system analysis and design, and troubleshooting tasks.

- **SELF-REGULATED LEARNING STRATEGIES.** These strategies refer to “actions directed at acquiring information or skill that involves agency, purpose (goals), and instrumentality self-perceptions by a learner” (Zimmerman & Martinez-Pons, 1986, p. 615). This study focuses on students’ use of cognitive (e.g., elaboration, organization, and critical thinking) and metacognitive (e.g., planning, monitoring, and regulating procedures) strategies.
- **SELF-REGULATION.** It is the ability of learners to control and adapt their cognition, behavior, and emotions in order to achieve a targeted goal (Schunk & Zimmerman, 1994; Zimmerman, 2000).
- **SYSTEM ANALYSIS AND DESIGN TASKS.** Real-world problems that require students to design systems, such as diagrams, tables, or flow charts, to represent relationships between variables (OECD, 2004).
- **TROUBLESHOOTING TASKS.** Real-world problems that require students to diagnose and repair faulty or underperforming systems (OECD, 2004).

CHAPTER 2 LITERATURE REVIEW

As stated in the first chapter, the present study aims to explore relationships between SRL and students' modeling outcomes by examining associations between self-efficacy beliefs, cognitive and metacognitive strategy use, and success on modeling tasks. This chapter provides a summary of research related to critical processes involved in mathematical modeling and SRL in three major sections. The first section involves an overview of a models and modeling perspective on mathematical learning and problem solving. The second section is devoted to a discussion of SRL from a social cognitive perspective to explicate the relationship between self-regulatory processes and mathematical problem solving. Finally, the last section presents a review of the research on two aspects of self-regulation, self-efficacy beliefs and students' use of cognitive and metacognitive strategies, and it argues for the positive effect of these constructs on students' problem-solving skills.

Mathematical Modeling

Mathematical modeling has been regarded as an effective platform for providing students with experiences that support them in developing mathematical knowledge and skills essential to succeed in life beyond school (English & Sriraman, 2010; Dark, 2003; Galbraith, Stillman, & Brown, 2010; Lesh & Zawojewski, 2007). During mathematical modeling, students work with tables of values, graphs, and charts to “describe, explain, or predict patterns or regularities associated with complex and dynamically changing systems” (Lesh, 2000, p. 179). They make sense of realistic situations by engaging in the processes of mathematization such as quantifying, organizing, sorting, weighting, and coordinating data. As such, students are provided with many opportunities to

exercise mathematical skills that are needed to understand real-world situations. This section provides a brief description of models, model-eliciting tasks, and modeling processes to illustrate the modeling view of mathematical problem solving.

Models

According to Hestenes (2010), models represent the structure of a problem-solving situation, which include the objects that make up a system as well as the relationships that exist between these objects. Students use models to solve and make predictions about complex problem-solving situations. Lesh and his colleagues also provided a similar definition and described models as

a system that consists of (a) elements; (b) relationships among elements; (c) operations that describe how the elements interact; and (d) patterns or rules.....that apply to the relationships and operations. However, not all systems function as models. To be a model, a system must be used to describe another system, to think about it, or to make sense of it, or to explain it, or to make predictions about it (Lesh et al., 2000, p. 609).

In a way, models represent how students are thinking, interpreting, or organizing information provided in a given situation. They are students' representations of their ideas, and these representations are both internal and external to them (Lesh & Doerr, 2003; Lesh, Doerr, Carmona, & Hjalmarson, 2003). In fact external representations such as verbal explanations, mathematical expressions, graphs, diagrams, computer graphics, or metaphors are descriptions of students' internal conceptual structures. The complexity or choice of a mathematical model is not a matter of concern provided it fits with a situation; the model can be as large as consisting of several representations or as small as a simple arithmetic equation or ordinary spoken language (Lesh & Doerr, 2003). Also, models need to be shareable, generalizable, and reusable in nature, which means that models should not only be used to describe a modeling situation for which it

is developed but should also be easily adaptable to understand similarly structured situations. Such models are produced when students repeatedly revise and refine their interpretations about the real-world situation (Lesh et al., 2000; Lesh & Doerr, 2003; Lesh & Lehrer, 2003). During this process of iterative refinement, students do not create just one model but develop a sequence of models that describe their ways of thinking about a complex modeling situation (Doerr & English, 2003; Larson et al., 2010). One form of such complex contexts, which is both model-eliciting and thought-revealing, is model-eliciting activities or MEAs.

Model-Eliciting Activities (MEAs)

MEAs are problem-solving activities that are based on real-life situations. These activities are carefully designed so that students can use their current mathematical knowledge and understanding to produce powerful, shareable, and re-usable models (Lesh, Yoon, & Zawojewski, 2007). Creation of such models involves identifying, selecting, and collecting relevant data, describing situations using a variety of representation media, and interpreting the solution repeatedly in the context of a real-world situation (Lesh & Doer, 2003). Modeling tasks are also called thought-revealing activities because models reveal how students are thinking, reasoning, explaining, comparing, or hypothesizing about mathematical objects, relations, and operations (Lesh et al., 2000). For example, one model-eliciting activity called “Big Foot” requires students to develop a procedure for police detectives that helps them to predict the height of a person from the size of a shoe print (Lesh & Doerr, 2003). The students were told that the procedure developed by them should work for all footprints. Lesh and Doerr reported that a group of students estimated the height to be about six times the size of the footprint by using trend estimation techniques rather than setting up a

proportion. These students recorded their height and shoe sizes as well as graphed the measurements by plotting the foot measurements on the x-axis and height measurements on the y-axis. The line of best fit helped students to determine a relationship between the size of a foot and height of a person. Thus, student-constructed models provide insight into students' understanding of mathematical concepts and relationships.

MEAs that provide students with opportunities to develop and test models in order to understand complex real-world mathematical problems are designed by taking into account six principles (Lesh et al., 2000). First, solutions to the modeling activities should require students to construct explicit models to describe, explain, and predict about patterns and regularities involved in the situations (the model construction principle). Second, the problem-solving tasks should be based on authentic situations that students could interpret using their current mathematical knowledge and skills (the reality principle). Third, modeling activities should include information that students could use to test and revise their thinking, create alternate solutions, and judge when and how their models need to be improved (the self-assessment principle). Fourth, the context of MEAs should encourage students to document and record their thinking about problem-solving situations, especially about the givens, goals, and possible solutions as they recursively move through each phase of the modeling cycle (the construct documentation principle). Fifth, models (e.g., spreadsheets, graphs, or graphing-calculator programs) developed by students should be shareable with other people as well as easily modifiable to make sense of situations structurally similar to the existing task (the construct shareability and reusability principle). Finally, models

produced by students should be based on useful metaphors (the effective prototype principle).

Modeling Processes

As stated above, students create models to understand and make predictions about modeling situations. The process of producing sophisticated models involves the extension of existing knowledge and understanding during which problem solvers repeatedly express, test, and modify their interpretations about these situations. Some important processes employed by effective students (or modelers) include “identification of flaws and ‘soft spots’ in the model, testing the trial model, understanding the limitations and better understanding the problem situation, revising the model, and testing it again” (Zawojewski, 2010, p. 239). These modeling processes support students in improving and refining their thinking about the nature of elements involved in the problem, relationships among elements, operations describing how the elements relate to one another, and understanding patterns or regularities in the problem-solving situations (Lesh & Lehrer, 2003).

Researchers in the field of mathematical modeling understand students’ use of modeling processes in terms of modeling cycles. A modeling cycle describes different stages that students have to pass through in order to provide solutions to real-world situations. Lesh and colleagues (Lesh & Doerr, 2003; Lesh & Zawojewski, 2007) proposed a modeling cycle comprised of four different stages including description, manipulation, prediction, and verification to illustrate ideal modeling behaviors (see Figure 2-1). Description involves understanding the structure of the real-world situation by comprehending texts, diagrams, graphs, charts, tables, or the context of the situation. It also represents behaviors involved in simplifying complex situations, such

as students making assumptions based on their prior knowledge. Manipulation refers to the act of developing a mathematical model through constructing hypotheses, critically examining mathematical details embedded within the task, and by mathematizing data. Prediction involves interpreting the actual situation based on the created model. Verification involves checking, evaluating, analyzing, and reflecting upon the predictions by considering real-world constraints as well as communicating results. The information gathered through this process supports students in refining and revising their thinking about the mathematical situation, which places them in the next cycle of the four-step modeling process. Students typically engage in a series of modeling cycles to generate productive interpretations about situations because givens and goal(s) are not clearly defined in modeling situations, and a single modeling cycle is not sufficient to understand a given situation, choose appropriate procedures, and create effective models (Haines & Crouch, 2010; Lesh & Doerr, 2003).

Research studies that examined students' reasoning with modeling data provide evidence that students go through multiple cycles of modeling processes to develop mathematical models that adequately describe complex modeling situations (Amit & Jan, 2012; Doerr, 2007; Doerr & English, 2003; English, 2006; Eric, 2009; Eric, 2010; Mousoulides, Christou, & Sriraman, 2008). Eric (2010) engaged three groups of sixth-grade students in a modeling activity: The Floor-Covering problem. The activity required students to choose carpet, tiles, or mats as the best covering material for a rectangular floor. Students selected the covering material by taking into account the dimensions of each material, cost per unit area of material, cost of loose material for patchwork, and labor expenses involved in cutting the material. They were also provided with actual

carpet, tiles, and mats to simulate the situation. Students' group discussions, written work, and reflections were used to determine the time spent by students in each phase of the modeling cycle. The timeline diagram across the various modeling stages described the modeling cycle to be iterative in nature. Students in all three groups (2 high-ability and 1 mixed-ability) chose the best covering material by repeatedly modifying their models, especially by moving cyclically around the four phases of description, manipulation, prediction, and verification as well as by revising their understanding of models within each of these four phases. Further, the timeline diagram indicated that the mixed-ability group students produced more model iterations, and students belonging to the high-ability groups revised their models a multiple number of times within a particular modeling phase (e.g., manipulation). The study also provides evidence that the creation and development of models are influenced by students' personal knowledge and experiences. For example, one of the high-ability groups recommended for using tiles over cheaper means of using a mat because they considered tiles to be more durable and allergy free compared to the carpets.

Doerr and English (2003) also reported that students solve modeling tasks by repeatedly refining their understanding of a modeling situation. They engaged four groups of middle-grade students in five mathematically equivalent activities to develop their understanding of the rating system, especially about ranking, sorting, selecting, and weighting data. The five modeling activities, including Sneakers, Restaurant, Weather, Summer camp, and Crime, involved developing a generalizable and reusable rating system often by creating and modifying quantities. For example, the Sneakers problem required students to develop a rating system for purchasing a pair of sneakers

by brainstorming important factors such as comfort, style, size, cost, brand, quality, and grip. In the Restaurant problem, participants were required to determine the most important factors influencing customers to revisit a restaurant based on the survey data of customers' rank preferences for fries, burgers, kids' meals, quickness, and price. Students' written work, records of small-group discussions, and field notes established that they engaged in multiple cycles of modeling to rank, select, and weight data, especially to describe situations and make effective decisions. Similar to Eric's (2010) study, students revised and refined their understanding of the real-world situation, quantities, and relationships between and among quantities at each stage of the modeling cycle. Further, the successive modeling cycles represented a progressive shift in students' ways of thinking and modeling solutions. For example, a group of students improved their ranking system of buying a pair of sneakers from 'nonmathematical rankings' consisting of personal preferences to 'frequency rankings', which involved ranking factors by taking into account the nonmathematical rankings of all the groups and aggregating the number of times factors occurred most frequently at the top two positions. However, when factors could not be ranked using frequency-ranking strategy, students used 'pairwise comparisons' to compare the relative order of the factors. These findings further prove when students are engaged in the successive sequences of the modeling cycle, they not only create efficient models but also develop a deeper understanding of the constraints and limitations associated with their models at each stage of the model development (Zawojewski, 2010).

Furthermore, students' approaches to these modeling problems indicate that MEAs are cognitively demanding tasks (Blum, 2011; English, 2010; Gailbraith, 2011),

and students need to work harder, persist longer, show greater interest in learning, and expend a lot of effort and time to produce possible solutions. Researchers who tracked students' models during their engagement with modeling tasks also claim that students typically spent two 40-minute class sessions to understand and describe a single modeling task (Doerr & English, 2003; Eric, 2009; Eric, 2011). Within the field of academic motivation, these behaviors are found to be associated with self-efficacy beliefs that refer to individuals' judgments of their own capabilities to accomplish a particular task (Schunk & Pajares, 2009). Also, there is considerable evidence in the problem-solving literature that higher sense of self-efficacy beliefs significantly affect students' learning, problem-solving achievement, self-regulation, amount of effort, and persistence on complex mathematical tasks (Chen, 2002; Nicolidau & Philippou, 2004; Pajares & Graham, 1996; Pajares & Krazler, 1995; Pajares & Miller, 1994). Given this literature, the present study hypothesized that self-efficacy beliefs would have positive effects on students' modeling task success.

The modeling problems used in the Doerr and English (2003) study emphasized the use of cognitive and metacognitive strategies. As mentioned earlier, students in this study developed rating systems for five different real-world situations by ranking quantities, identifying relationships between and among quantities, and selecting appropriate operations and representations. Such notions of ranking, sorting, selecting, organizing, transforming, and weighting data may require the use of cognitive strategies. Specifically, elaboration strategies may be useful in summarizing data sets or information provided in the problem, explaining ideas to others, noting important points, and negotiation of conjectures and clarification of explanations. Organization

strategies may be useful in transforming and organizing information in meaningful ways, modifying quantities, and ranking multiple factors. Describing, explaining, and predicting actual situations with the help of rating systems (or models) may require the use of critical thinking strategies. Metacognitive strategies may play an active role when students refine their models during multiple cycles of interpretations, descriptions, conjectures, explanations, and justifications. Additional studies that examine the role of cognitive and metacognitive strategies in mathematical modeling will be discussed in the next section.

Summary

Researchers (e.g., Blum, 2011; English & Sriraman, 2010; Lesh & Zawojewski, 2007) as well as current mathematics standards (e.g., CCSSM) argue for engaging students in mathematical modeling to provide them with opportunities to use and apply mathematical knowledge and skills in solving real-world situations. Modeling tasks are complex problem-solving activities that are solved by iteratively creating, testing, and revising models. Models are students' representations of their ideas that describe how they are thinking, organizing, and interpreting information provided in the modeling tasks (Lesh & Doerr, 2003). Students use modeling processes to understand and solve these real-world problems (Lesh et al., 2000). Modeling processes include explaining the problem, describing the problem, building a mathematical model, connecting the model with the real-world situation, predicting real-world problems, and verifying the solution within the context of the real-world situation. A brief review of research focused on designing and tracking students' responses on modeling activities informs us that self-efficacy beliefs and SRL strategy use may influence students' success in solving modeling tasks. Self-efficacy beliefs may influence students' performance, persistence,

and efforts in solving complex modeling tasks. The self-reported use of SRL strategies, such as cognitive and metacognitive strategies, may support learners in interpreting real-world situations and developing efficient models. In order to test these hypotheses, the present study examined associations between self-efficacy beliefs, cognitive and metacognitive strategy use, and students' success in modeling tasks. The next section describes the importance of self-regulatory processes that play a major role in students being active agents of their own learning process.

Self-Regulatory Processes and Problem Solving

In this section, self-regulation is discussed from a social cognitive perspective, which may provide a useful framework to understand the proactive and independent working style of students engaged in mathematical modeling. Modeling as a Standard for Mathematical Practice requires students to apply their mathematical knowledge and skills to solve problems arising in a real-world environment. Self-regulation theory may help us to understand how students engaged in complex modeling activities control and regulate their behaviors during iterative modeling cycles.

Social cognitive theory defines self-regulated students as “metacognitively, motivationally, and behaviorally active participants in their own learning process” (Zimmerman, 1989, p. 329). Such students regulate their motivation and behaviors by establishing realistic and attainable learning goals, monitoring and assessing progress towards these goals, and setting revised goals and actions (Zimmerman, 1989, 2000). In general, social-cognitive theory views self-regulation as (1) an interaction among personal, behavioral, and environmental factors, and (2) comprised of cognitive and metacognitive processes as well as self-motivational beliefs.

Triadic Reciprocal Interactions

A central tenet of social cognitive theory is that human functioning involves reciprocal interactions among personal, behavioral, and environmental factors (Bandura, 1997; Zimmerman, 2000). During these triadic interactions, problem solvers not only control their behaviors and environments but also are influenced by them. Personal variables include covert processes (e.g., cognitive and metacognitive processes), beliefs (e.g., self-efficacy beliefs), and affective factors (e.g., perceptions of satisfaction or dissatisfaction) that students use to acquire knowledge and skills (Zimmerman, 1989). Behavioral factors involve making changes in behavior to improve learning, overcoming anxiety, and reducing perceptions of low self-efficacy (Zimmerman, 1989, 2000). Examples of critical behaviors are keeping track of problem-solving strategies through journal writing, self-evaluating performances, making appropriate choices, increasing effort or persistence toward the task, and verbalizing thoughts. Environmental factors comprise the social and physical environment of the problem solver such as the nature of the task posed, statements communicated, or feedback provided by the environment including teachers.

The triadic model assumes that personal, behavioral, and environmental variables are distinct from each other but constantly influence each other in a reciprocal fashion. For example, the environment influences behavior when a teacher shares a modeling task with the students and directs their attention (behavior) toward it. Behavior affects the environment when students do not understand the complex mathematical task and the teacher (environment) supports students to understand the task through scaffolding. Students' behaviors such as the use of cognitive and metacognitive strategies raise their self-efficacy beliefs for solving tasks, which further influence

personal factors such as increased persistence as well as effort expended in interpreting modeling tasks. The social cognitive theory presents a view of personal agency through which students exert control over their thoughts, feelings, and actions (Schunk & Pajares, 2005). Researchers have found that effective and ineffective problem solvers regulate and control aspects of personal, behavioral, and immediate learning environments differently (Clearly & Zimmerman, 2001).

Cyclical Phases of Self-Regulation

The social cognitive theory of self-regulation segments behaviors aimed toward accomplishing a task into three phases including forethought, performance, and self-reflection that are associated with specific cognitive and metacognitive strategies (Zimmerman, 2002; Zimmerman & Campillo, 2003) (see Figure 2-2).

Forethought phase

The forethought phase processes involve planning and preparation efforts before engaging in a task. Self-regulated students proactively engage in goal setting and strategic planning by analyzing the problem-solving task, setting realistic goals, and activating problem-solving strategies (Zimmerman, 2002). Carefully selected methods and strategies enhance students' cognition, affect, and motoric execution (Zimmerman & Campillo, 2003). Self-regulatory processes are influenced by several self-motivational beliefs including students' beliefs in their abilities to accomplish a task (self-efficacy beliefs), their beliefs about the future benefits of engaging in a task (outcome expectations), their natural interest in a topic (intrinsic interest), and their general reasons for engaging in a task (goal orientation).

The present study focused particularly on self-efficacy beliefs, which refer to individuals' perceptions of their own capabilities to accomplish a particular task

(Bandura, 1997). In academic settings, particularly school mathematics, self-efficacy refers to students' judgments of their abilities to solve mathematics problems, perform mathematics-related tasks, or engage in mathematical activities (Pajares, 1996). Self-efficacy beliefs are task- and situation-specific judgments, which are reported in relation to a goal (Pajares, 2008). For example, students may hold high self-efficacy beliefs for solving routine mathematics problems that require procedural knowledge of basic mathematics rules and low efficacy beliefs for solving real-world problems that require conditional knowledge of when to use a particular mathematical rule or strategy. This is because one's efficacy beliefs stem from several factors such as the nature of the tasks, amount of effort required, skills needed, and environmental factors. These beliefs reflect students' judgments of performing a task in future rather than their actual performance level. In actual reporting, students may underestimate or overestimate their judgments about their own competence (Pajares & Miller, 1994; Pajares & Kranzler, 1996; Schunk & Pajares, 2009). Poor calibration mainly occurs because students fail to understand the complexity involved in the task and cognitive demands posed by it (Schunk & Pajares, 2009).

Academic self-efficacy plays an important role during the three phases of self-regulation (Schunk & Ertmer, 2000; Zimmerman, 2002a). During the forethought phase, self-efficacy beliefs influence goal setting as well as the strategies selected to accomplish a task (Schunk, 2000). Students with high self-efficacy beliefs set proximal and challenging goals, whereas those with low efficacy tend to stay away from difficult tasks (Schunk, 1983a; Zimmerman, Bandura & Martinez-Pons, 1992). Additionally, self-efficacious problem solvers set "learning goals, use effective learning strategies,

monitor comprehension, evaluate goal progress, and create supportive learning environment” (Schunk & Mullen, 2012, p. 222). Thus, motivational beliefs impact the extent to which students engage in self-control and self-observation processes of the performance phase.

Performance phase

Performance phase processes come into play when students are actually involved in doing a task, such as solving a mathematics problem or preparing for a test. Self-regulated students utilize several self-control processes, such as self-instruction, attention focusing, and task strategies, to increase their focus, attention, and persistence towards the task (Zimmerman & Campillo, 2003). Specifically, they control their cognition by employing cognitive strategies such as organization, elaboration, and critical thinking. They manage their behaviors and actions by using self-instruction strategies such as overt or covert self-verbalization. Self-observing or monitoring processes closely follow the self-control processes. Self-monitoring involves tracking one’s performance purposefully, especially to diagnose errors and mistakes in their methods and strategies (Cleary & Zimmerman, 2012). These processes inform students about their progress toward their goals and motivate them to adjust their strategies and behaviors as necessary. Further, the extent to which students use these processes is governed by the beliefs they hold about their own capabilities. Self-efficacious students during their engagement with tasks use productive problem-solving strategies and are more likely to monitor their performances as well as assess their progress toward goals (Schunk & Mullen, 2012). They work harder, persist longer, and persevere in difficult times (Pintrich, Roeser, & DeGroot, 1994; Zimmerman & Martinez-Pons, 1990).

Self-reflection phase

The self-reflection phase is contingent upon cognitive and behavioral monitoring and tracking of the problem-solving steps. Effective students improve their learning strategies and problem-solving performance by engaging in processes such as self-judgment and self-reaction. Specifically, during this phase students evaluate their progress by comparing their current performances with their previous achievements and by tracking the ways in which they have improved (Zimmerman, 2000; Zimmerman & Campillo, 2003). Self-evaluative judgments are closely linked to the attributions students make for their successes and failures. These attribution judgments play a crucial role during the self-reflection phase, as students who attribute the cause of their failures to low ability react negatively and refrain from engaging in the same task with greater effort. On the contrary, students who attribute their mistakes to poor problem-solving strategies believe that they can correct their mistakes by improving their strategies. Further, it is important to note that students who are confident in their abilities attribute their poor performance to the lack of effort or strategy use. Additionally, they are more likely to revise their strategies and goals.

Summary of the Self-Regulation Processes

The social cognitive view of self-regulated learning postulates that human functioning occurs as a result of the reciprocal interaction between personal, behavioral, and environment factors (Zimmerman, 2000). During this interaction, each of the three factors not only influences the other two factors but also is affected by them. The theory also hypothesizes that self-regulatory processes and motivational beliefs are enacted within three cyclical phases of forethought, performance, and self-reflection (Zimmerman & Campillo, 2003). During the forethought phase, self-efficacious problem

solvers analyze the task and plan strategically to accomplish self-set goals.

Performance phase processes facilitate students' progress toward their goals. Students who believe in their academic abilities use effective learning strategies for learning the material as well as adjust their strategies and methods by engaging in self-observation and self-monitoring procedures. Self-reflection processes involve students' reactions to their learning outcomes, especially how they performed against a self-set goal.

Inconsistencies between the established goals and actual performance guide problem solvers to modify and revise their goals and strategies, which places them into the next SRL cycle (Clearly & Zimmerman, 2012).

Furthermore, these behaviors are structurally similar to the modeling behaviors exhibited by students who are engaged in the successive modeling cycles. During these modeling cycles, students iteratively test, revise, and modify their mathematical interpretations until they develop a model that adequately describes a modeling situation. Similar to self-regulated learners, students engaged in complex modeling activities are typically required to analyze tasks, select appropriate mathematical concepts and operations to mathematize realistic situations, create and keep track of their models, and refine their interpretations iteratively when the created model(s) fails to predict the actual situation (Amit & Jan, 2010; English, 2006; Eric, 2010; Mousoulides et al., 2010). Because self-regulation involves proactive processes and beliefs to acquire self-set goals (Zimmerman, 1989), SRL behaviors and motivational beliefs may play an important role during students' independent engagement with the real-world modeling problems. The present study hypothesized that these behaviors and beliefs might be associated with students' modeling outcomes. The next section argues for

these relationships through an examination of associations between self-efficacy beliefs, self-regulatory strategies, and problem-solving (or modeling) achievement.

Self-Regulation and Mathematical Problem Solving

In this section, self-efficacy beliefs and SRL strategies will be explained. The first subsection describes research studies that explored correlations between self-efficacy beliefs and students' problem-solving performance. Additionally, studies will be discussed that established correlations between self-efficacy beliefs with students' reported use of cognitive and metacognitive strategies. The second subsection includes a review of studies that explored associations between students' self-reported use of cognitive and metacognitive strategies and their performance on academic tasks.

Self-Efficacy Beliefs and Mathematical Problem Solving

As stated earlier, the social cognitive theory highlights that human functioning occurs as a result of reciprocal interactions among personal variables, behavioral factors, and environmental influences. Further, the theory states that proactive, self-reflecting, and self-regulated learners have the capacity to take control of their thoughts, feelings, and actions. According to Bandura (1997), self-regulated learners display this sense of personal agency because of the beliefs they hold about themselves and their capabilities. The present study is interested in understanding the influence of self-efficacy perceptions on students' ability to correctly solve real-world or modeling tasks.

Research shows that self-efficacy beliefs correlate positively with students' academic achievement and problem-solving success (Chen, 2003; Greene, Miller, Crowson, Duke, & Alley, 2004; Nicolidau & Philippou, 2004; Pajares, 1996; Pajares & Graham, 1999; Pajares & Kranzler, 1995; Pajares & Miller, 1994, Pajares & Valiante, 2001; Pintrich & DeGroot, 1990). For example, Pajares and Miller (1994) measured

mathematics confidence in 350 college undergraduate students. Participants also reported their mathematics self-concept, mathematics anxiety, perceived usefulness of mathematics, prior experience (number of years/semesters in mathematics), and mathematics performance. Students' mathematics performance was measured through a test composed of items from the National Longitudinal Study of Mathematics Abilities (Pajares & Miller, 1994). Correlations between all independent variables (e.g., self-confidence, self-concept, mathematics anxiety, perceived usefulness, and prior experience) and mathematics performance were found to be significant. However, students' self-beliefs about their capabilities to solve problems were found to be the most predictive of their actual ability. In fact, self-efficacy had stronger direct effects on performance than any other variable.

The previous study was replicated and extended by examining the role of self-efficacy beliefs in a high school setting and by taking into account students' general mental ability (Pajares & Kranzler, 1995). Two hundred and seventy three high school students reported their mathematics self-efficacy and mathematics anxiety. Researchers also collected information about students' general mental ability through their performance on a general reasoning ability test. Students' mathematics performance was measured through a problem-solving test consisting of 18 items focusing on arithmetic, algebra, and geometry. The correlations between mathematics self-efficacy beliefs, mathematics ability, anxiety, prior experience, and mathematics performance were found to be significant. Moreover, Pajares and Kranzler found stronger direct effects of students' self-efficacy beliefs on mathematical problem-solving performance even after controlling for general mental ability. Pajares further reported

that self-efficacy beliefs are helpful in predicting the problem-solving performance of not only college and high school students but also middle-grade students (Pajares & Graham, 1999).

Self-efficacy beliefs are more strongly related to students' problem-solving achievement when other factors, such as students' attitudes toward mathematics, are studied within a statistical model (Nicolidau & Philippou, 2004). In this study, 238 fifth-grade students reported their self-efficacy beliefs and attitudes toward mathematics. Students' problem-solving achievement was measured in terms of their success on a test consisting of 10 word problems and 10 routine problems. In agreement with research findings discussed above, researchers found that self-efficacy beliefs had stronger direct effects on students' problem-solving performance ($\beta = .55, p < .001$) than their attitudes toward mathematics ($\beta = .37, p < .001$).

Self-efficacy beliefs not only influence problem-solving achievement directly but also indirectly through their influence on students' use of cognitive and metacognitive strategies (Bouffard-Bouchard et al., 1991; Heidari et al., 2012; Pintrich & DeGroot, 1990; Zimmerman & Bandura, 1994). In a study involving 173 seventh-grade students, Pintrich and De Groot (1990) examined the correlations between students' motivational orientation (e.g., self-efficacy beliefs), self-regulated learning strategy use (e.g., cognitive, metacognitive, and effort management strategies), and academic performance in science and English classrooms. The Motivated Strategies for Learning Questionnaire (MSLQ) consisting of 56 items was used to collect data related to self-efficacy beliefs and SRL strategies. Academic achievement data were collected through students' performance on classroom tasks and assignments. Higher academic self-

efficacy was associated with students' reported use of cognitive engagement and performance. This implies that students who report high levels of academic self-efficacy would also report using various cognitive and self-regulative metacognitive strategies, and they were more likely to persist under difficult learning activities. Self-efficacy judgments, however, were not associated with students' academic performance on seatwork, academic essays, and exams when cognitive variables were included in the statistical analyses. Based on these findings, Pintrich and De Groot concluded, "self-efficacy beliefs play a facilitative role in relation to cognitive engagement" (p. 37). Zimmerman and Bandura (1984) also reported that self-efficacy for writing influence students' performance both directly as well as indirectly through personal goal setting. Approximately 95 college undergraduates reported on two questionnaires that measure their self-efficacy for writing as well as the extent to which they regulate their writing activities (e.g., planning, organizing, and revising compositions). Self-efficacy and goal setting together accounted for 35% of the variance in academic achievement.

These findings were supported in other subject areas (e.g., English) as well (Greene et al., 2004). A total of 220 high school students responded to a self-report questionnaire measuring their self-beliefs, use of cognitive strategies, mastery goals, performance goals, and academic achievement in English classes. Self-efficacy and use of meaningful strategies had the strongest direct effect on students' academic achievement among other variables such as mastery and performance goal orientations. Further, self-efficacy beliefs positively influence students' use of meaningful strategies as well as indirectly affect students' academic achievement through their use of cognitive strategies. Supporting these findings, Bouffard-Bouchard

et al. (1991) also reported a positive association between self-efficacy beliefs and students' SRL behaviors. They engaged 45 high-school junior and 44 high-school senior students in nine comprehension tasks involving replacement of irrelevant words with meaningful words. Students' self-efficacy beliefs were correlated with several dependent variables such as the number of times they checked the time (monitoring of time), their persistence over a task, self-evaluation, and their performance on the test. Students who believe in their English reading comprehension skills were found to display greater performance monitoring, task persistence as well as performed better on the comprehension tasks than students with low self-efficacy beliefs.

Nevill (2008) also found significant correlations between reading self-efficacy beliefs and regulation of cognition. A convenience sample of 84 elementary students reported their self-efficacy beliefs on a reading scale called The Reader Self-Perception scale. The researcher rated students' metacognitive behavior on a scale called Behavior Rating Inventory of Executive Function. Further, students' reading achievement was measured on an oral reading fluency test. Nevill reported that students who were self-efficacious about their reading abilities were more likely to regulate their thought processes than students who held low self-efficacy beliefs in reading. Similar findings were reported by another study involving 50 high-school junior Iranian students majoring in English translation (Heidari et al., 2012). Students responded to a self-efficacy belief questionnaire and vocabulary learning strategy questionnaire. High self-efficacy beliefs significantly correlated with more diverse use of vocabulary learning strategies. Based on these results, researchers concluded that

students who believed they were capable of reading would use vocabulary strategies more frequently and effectively.

Taking into account the positive correlations established between students' perceived self-efficacy beliefs and academic performance, the present study extended past research by exploring the influence of self-efficacy beliefs on students' performance in solving modeling tasks. The indirect effects of self-efficacy beliefs on students' modeling success through their use of cognitive and metacognitive strategies were also investigated. The next section describes associations between SRL strategies (e.g., cognitive and metacognitive strategy use) and mathematical problem-solving success.

Cognitive and Metacognitive Strategies

Learning strategies refer to students' strategic approaches to understand and solve academic tasks (Garcia & Pintrich, 1994). Zimmerman and Martinez-Pons (1986) define SRL strategies as "actions directed at acquiring information or skill that involve agency, purpose (goals), and instrumentality self-perceptions by a learner" (p. 615). Although self-regulated students utilize various strategies, the present study focused on the use of cognitive and metacognitive strategies. Cognitive strategies are learning strategies that influence students' processing of information, for example elaborative, organization, and critical thinking (Pape & Wang, 2003; Pintrich & De Groot, 1990; Pintrich et al., 1993; Zimmerman & Martinez-Pons, 1986, 1988, 1990). Elaborative strategies are higher-order learning strategies that support students' acquisition of information by integrating new material with existing knowledge (Ormord, 2008; Schunk & Zimmerman, 1998). Some elaborative strategies used by effective problem solvers include paraphrasing or summarizing material, creating analogies, productive note

taking, explaining the material to others, and asking or answering questions to clarify understanding or improving comprehension (Kitsantas & Dabbagh, 2010). These strategies may be useful to understand modeling activities, where students are required to make sense of real-world situations using their current mathematical knowledge and skills.

Similar to elaborative strategies, organizational strategies also help students in building connections between different ideas as well as to arrange the material meaningfully (Ormord, 2008). Organizational strategies, such as selecting and outlining important ideas or topics, developing concept maps, or representing concepts graphically, support students in distinguishing relevant from irrelevant material and in placing similar ideas together. These strategies may be helpful in mathematizing realistic modeling tasks, which include sorting, quantifying, organizing, and selecting large data sets.

In addition to cognitive strategies, metacognitive strategies may influence students' learning and problem-solving performance (Pape & Wang, 2003; Pintrich & De Groot, 1990; Pintrich et al., 1993; Zimmerman & Martinez-Pons, 1986, 1988, 1990). Metacognitive strategies are typically comprised of three different types of processes including planning goals, monitoring actions, and regulating strategies or methods. Planning strategies assist students in analyzing the task as well as setting appropriate goals, especially by activating existing knowledge and experiences. These strategies may help students in organizing their thoughts, and selecting concepts and strategies useful in understanding modeling tasks.

Monitoring strategies focus students' attention on the task and prompt them to keep track of their strategies and actions. Students may monitor their work by tracking their attention while working on a task or using questions to check their understanding of the task. These strategies may help students in evaluating their thinking about a modeling situation or finding limitations in their models. Regulating strategies are closely connected to the monitoring strategies, as they involve students' reactions to the evaluative judgments made using monitoring strategies. These strategies may help students in improving their models because they encourage them to modify their strategies or methods of inquiry by acquiring more information or reviewing initial models.

Similar to academic self-efficacy, learning strategies also influence the cyclical phases of self-regulation. Specifically, strategic students analyze the task, develop learning plans to achieve their academic goals, choose task appropriate strategies, and organize, monitor, and regulate their thought processes throughout the three phases. Several researchers have reported that cognitive and metacognitive strategy use is related to as well as predictive of students' problems-solving and academic performance (Pape & Wang, 2003; Pintrich, 1989; Pintrich & De Groot, 1990; Verschaffel et al., 1999; Zimmerman & Martinez-Pons, 1986, 1988, 1990). For example, Pintrich and De Groot (1990) reported that seventh-grade students' reported use of cognitive (e.g., elaboration, organization and critical thinking) and self-regulative metacognitive strategies were significant predictors of their academic performance in science and English classes. Zimmerman and Martinez-Pons (1986) also reported similar results in a study with 40 high-school students. They explored the learning

strategies used by high- and low-achieving students during learning. Participants reported use of learning strategies in relation to six problem situations were categorized into 14 self-regulated behaviors, such as self-evaluation, organization and transformation, goal setting and planning, keeping records, and monitoring. Researchers found that high- and low-achieving groups differed significantly in their strategy use, frequency of using each strategy, and consistency of using a particular strategy. Specifically, high-achieving students reported greater use of all SRL strategies such as organizing, transforming, maintaining records, and monitoring.

In a study with middle-grade students, Pape and Wang (2003) examined sixth- and seventh-graders' reported use of strategies and relationships between strategy use, academic achievement, problem-solving behaviors, and problem-solving success. On a self-report Strategy Questionnaire adapted from Zimmerman and Martinez-Pons' (1986) study, students reported the strategies they used during reading and mathematical problem-solving situations, frequency of using these strategies, and confidence in using these strategies. Students' mathematical problem-solving behavior and success in problem solving were examined by engaging them in videotaped think-aloud sessions. The high and low achievement group students did not differ significantly in relation to the number of strategies used, frequency of using each strategy, and confidence ratings. However, high-achieving students used more sophisticated strategies than low-achieving students with respect to mathematical problem-solving situations. For example, they solved mathematics problems by understanding the context of the problem as well as by transforming information into meaningful representations.

Some traces of students' use of cognitive strategies are also found in modeling studies that examined students' use of mathematization processes, such as sorting, quantifying, categorizing, dimensionalizing, and weighting data, in simplifying situations and building models (Doerr & English, 2003; English, 2006; Eric, 2009, Mousoulides, Pittalis, Christou, & Sriraman, 2010). English (2006) examined sixth-grade students' mathematization processes by understanding how they modeled a situation involving creation of a consumer guide for deciding the best snack chip. During the study, students were engaged in whole-class discussions focusing on the "notion of consumers, various consumer items, criteria that consumers might consider in purchasing an item, and the nature of consumer guides" (English, 2006, p. 308). Students sort and organize data by identifying and ranking important factors related to the snack (e.g., chip size, cost, freshness, moistness, crunchiness, guarantee, and quality), assigning and negotiating ratings, quantifying qualitative data such as taste, raising sample issues, and revising strategies repeatedly to prepare a consumer guide. Such actions and behaviors may require the use of cognitive strategies. Specifically, students may need to use elaboration strategies to select relevant material, organization strategies to arrange information meaningfully, and critical thinking strategies to critically interpret quantitative data. Further, decisions involving revisions of models may involve critical and logical decision-making.

Mousoulides et al. (2010) showed that older students (e.g., 8th-grade) are more likely to employ superior mathematization processes and produce more efficient models in comparison to younger students (e.g., 6th-grade). Researchers in this study compared and contrasted the modeling and mathematization processes of sixth- ($n = 19$) and

eighth-grade ($n = 18$) students in understanding a “University Cafeteria” problem that required them to choose three part-time and three full-time vendors based on the number of hours worked and money collected by nine vendors. Students in both the grades engaged in several mathematization processes to organize and explore data as well as to rank and select employees. However, eighth-grade students presented more refined and sophisticated models as they considered all the relevant variables and possible relationships to identify patterns and relations. Further, 6th-grade students did not verify their models in the real-world context, whereas 8th graders interpreted their models several number of times within the context of the situation to select employees. These students also indulged in metacognitive activity such as reflecting and revising models based on the suggestions provided by others (e.g., teacher or teammates). Further, the time spent (four 40 minute sessions) by students in both the groups to find a solution for the problem indicated that modeling problems require a lot of time and effort.

Furthermore, the iterative process of describing, testing, and revising models requires the use of metacognitive skills such as planning, monitoring, and revising strategies or solutions. Blum (2011) also argues, “metacognitive activities are not only helpful but even necessary for the development of modeling competencies” (p. 22). The importance of metacognitive knowledge and strategies during mathematical modeling can be found in studies conducted by Kramarski and his colleagues investigating the influence of metacognitive instruction in understanding real-world problems (e.g., Mevarech & Kramarski, 1997; Kramarski, Mevarech, & Arami, 2002; Kramarski, 2004). In an attempt to support students in understanding authentic mathematical tasks,

Kramarski et al. (2002) engaged seventh-grade ($N = 91$) students in two different types of learning environments, cooperative learning with metacognitive instruction and cooperative learning with no metacognitive instruction.

In the cooperative-metacognitive condition, students were provided experience in using metacognitive questions to discuss and solve standard mathematics problems. Metacognitive questions focused on the cognitive processes of comprehending the problem (e.g., what is the problem all about?), constructing connections between new and previously solved problems (e.g., what are the similarities or differences between the current and already solved problem?), using appropriate strategies (e.g., what are the strategies/tactics/principles appropriate for solving the problem and why?), and reflecting (e.g., what did I do wrong here?). Students in the cooperative learning group discussed the problems in a group without undergoing any training on using metacognitive questions. Each student shared his/her solution process with the whole group and discussed the problem collectively to provide a common solution. The effect of the cooperative-metacognitive learning environment was evaluated by testing students on authentic and standard mathematical tasks prior to and following the intervention.

The authentic tasks used by Kramarski and his colleagues align very closely with the decision-making tasks used in the PISA 2003 assessment. For example, the posttest problem involved ordering pizzas for a party after considering a variety of information such as the price of the pizza, size of the pizza, and the number of toppings. These tasks required students to make a decision after taking into account a host of different factors as well as considering several constraints. The standard mathematical

test involved 41 multiple-choice questions focusing on whole numbers, fractions, decimals and percentages. Students in the cooperative-metacognition group scored better on authentic and standard tasks, and they provided better justifications than the students in the cooperative group. Further, both high and low achievers in the cooperative-metacognitive group outperformed their peers in the cooperative group.

In a follow-up study, Kramarski (2004) examined the effect of cooperative-metacognitive environment on students' ability to construct and interpret graphs. Eighth-grade students were either placed into cooperative learning environments or cooperative-metacognitive learning environments. In each environment, students learned several graphical concepts including understanding of slope, intersection point, and rate of change as well as various methods of interpreting graphs. Metacognitive instruction significantly enhances students' ability to construct and interpret graphs. The students trained in metacognitive instruction were also found to possess less alternative conceptions about graph interpretation.

In contrast to these experimental studies, Magiera and Zawojewski (2011) investigated the influence of metacognitive knowledge using an exploratory approach. They claimed that small-group mathematical modeling provides contexts for activating metacognitive aspects of thinking because during these discussions students interpret diverse perspectives of group members, explain and justify their own reasoning, and seek mathematical consensus. Magiera and Zawojewski examined the metacognitive behaviors of three ninth-grade students within a collaborative learning environment where they collectively solved five modeling problems. After the problem solving was complete, students watched the video records of each modeling session to explain and

justify their thought processes about understanding and solving modeling problems. Students' metacognitive behaviors were established by coding transcribed interviews into metacognitive awareness, evaluation, and regulation. The frequency of occurrence of each behavior was also noted. Students predominantly engaged in metacognitive evaluation and regulation followed by awareness of their thought processes. Based on this literature, the present study hypothesized the positive effect of self-reported use of cognitive and metacognitive strategies on students' modeling outcomes.

Summary

In this section, three components of SRL: Self-efficacy beliefs, cognitive strategies, and metacognitive strategies were described along with their influence on students' problem-solving performance and achievement. Students who believe in their competence set challenging goals, select productive strategies, persist longer and expend more effort toward academic tasks (Schunk & Pajares, 2008). Efficacious students are also more likely to correctly solve problem-solving tasks (Pajares & Miller, 1995). Cognitive and metacognitive strategies, which support students in organizing thought processes as well as in planning, monitoring, and regulating problem-solving behaviors, were also described. Several studies have found self-reported use of cognitive and metacognitive strategies to be correlated with students' problem-solving achievement (Pape & Wang, 2003; Pintrich & De Groot, 1990; Zimmerman & Martinez-Pons, 1986, 1988, 1990). The use of metacognitive questions has been found to be useful in solving authentic and real-world mathematical tasks (Mevarech & Kramarski, 1997; Kramarski et al., 2002; Kramarski, 2004). Further, academic self-efficacy facilitates the use of cognitive and metacognitive strategies (Bouffard-Bouchard et al., 1991; Pintrich & DeGroot, 1990). Based on the review of literature, this study examined

associations between self-efficacy beliefs, cognitive and metacognitive strategy use, and students' success in solving three different types of modeling problems including decision-making, system-analysis and design, and troubleshooting.

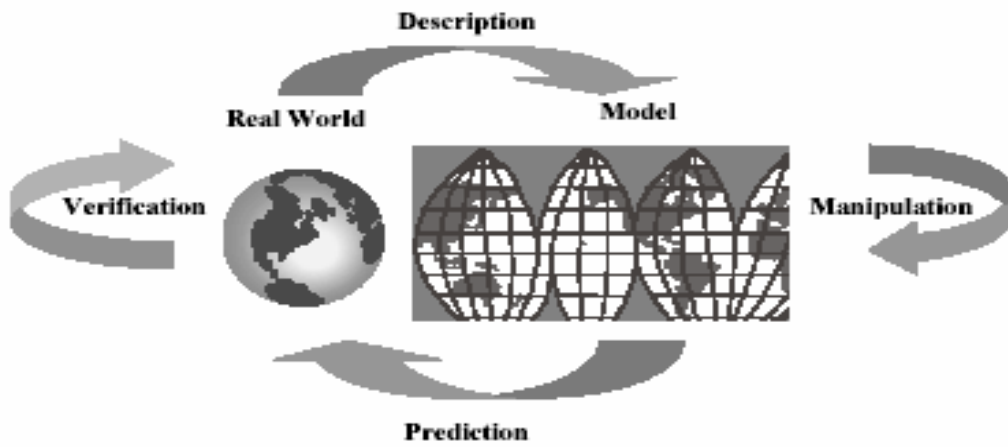


Figure 2-1. Modeling cycles often involves four basic steps including description, manipulation, prediction and verification (Lesh & Doerr, 2003, p. 17)

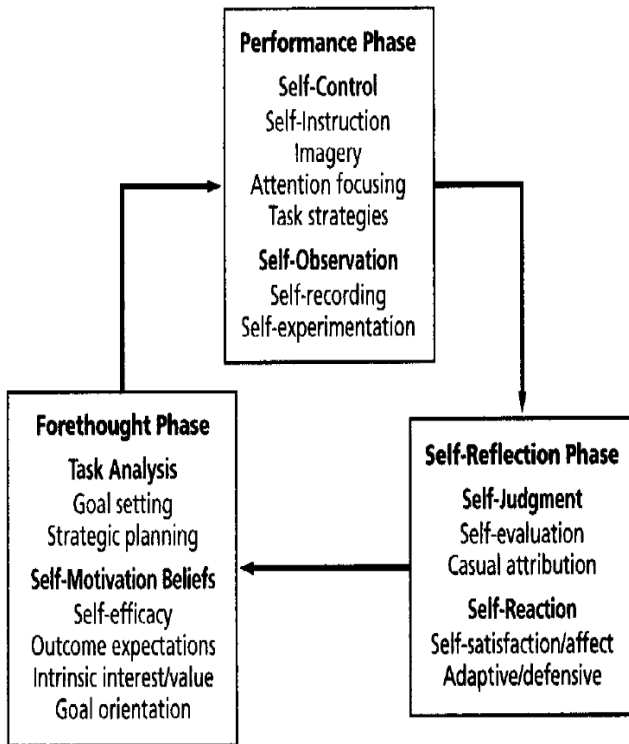


Figure 2-2. Phases of self-regulation (Zimmerman, 2002, p.13)

CHAPTER 3 METHOD

Introduction

The goal of this study was to gain understanding of the relationships between SRL and mathematical modeling by examining how self-efficacy beliefs, cognitive strategies, and metacognitive strategies were associated with students' success rates on solving modeling tasks. Based on the purpose of the present study, three key research questions were investigated.

Research Questions

1. What are the direct effects of students' self-efficacy beliefs for modeling tasks on their performance on modeling tasks?
2. What are the direct effects of students' self-reported use of cognitive and metacognitive strategies on their performance on modeling tasks?
3. What are the indirect effects of students' self-efficacy beliefs for modeling tasks on their performance on modeling tasks through their effects on their use of cognitive and metacognitive strategies?

Research Hypotheses

Past research studies have reported a positive correlation between self-efficacy beliefs and problem-solving achievement (Hoffman & Spataru, 2008; Pajares, 1996; Pajares & Graham, 1999; Pajares & Kranzler, 1995; Pajares & Miller, 1994, Pintrich & DeGroot, 1990). These studies provide evidence that students' beliefs about their competence are a significant predictor of their problem-solving success even after controlling for mental ability (Pajares & Kranzler, 1995) and mathematics anxiety (Pajares & Graham, 1999). Efficacy judgments positively influence students' engagement and persistence with complex tasks as well as amount of cognitive effort exerted during problem-solving activities (Schunk & Mullen, 2012; Schunk & Pajares,

2009). Self-regulated learning strategies such as cognitive and metacognitive strategies also correlate positively with students' academic achievement and problem-solving skills (Pape & Wang, 2003; Pintrich & De Groot, 1990; Pintrich et al., 1993; Zimmerman & Bandura, 1994; Zimmerman, & Martinez-Pons, 1986, 1988, 1990). Cognitive strategies such as elaboration, organization, and critical thinking influence students' processing of information, which further helps them to better understand the problem and create superior solutions. Pintrich and colleagues (e.g., Pintrich, 1989; Pintrich et al., 1991) found that students who report using more cognitive and metacognitive strategies solve more problem-solving tasks correctly and receive higher grades. Further, they reported that students who believe in their abilities are more cognitively engaged and display greater use of cognitive and metacognitive strategies in solving mathematics problems (Pintrich & De Groot, 1990). Similar results were reported by Bouffard-Bouchard et al.(1991), who found that high-school students with high self-efficacy beliefs for academic tasks displayed greater monitoring on academic performance and persisted longer than students with low self-efficacy beliefs.

Given the literature in the field, a statistical model was developed that hypothesizes relationships between students' self-efficacy beliefs, cognitive and metacognitive strategy use to their performance on a modeling test (see Figure 3-1). Based on the literature, three hypotheses were proposed for this study. First, it was hypothesized that students' self-efficacy beliefs for the modeling tasks would have a positive direct influence on their ability to correctly solve problems on the modeling test. Second, it was hypothesized that students' self-reported use of cognitive and metacognitive strategies would directly influence their performance on the modeling

test. Third, it was hypothesized that students' self-efficacy beliefs for modeling tasks would have a positive indirect influence on their performance on modeling tasks through the positive effect on their use of cognitive and metacognitive strategies.

Pilot Study

In order to answer these research questions, two major steps were taken related to data collection procedures. First, problems from the PISA problem-solving assessment were revised to contextualize them within participants' immediate surroundings. Second, a Modeling Self-Efficacy scale was developed to collect data about participants' confidence in solving modeling problems. A pilot study was conducted to test the psychometric properties of this scale including item analysis, internal consistency, content validity, and construct validity.

Participants

One hundred and fifty one 10th-grade students were selected through convenience sampling from three different locations. Out of these, 91 students between the ages of 15 and 18 were engaged from a local research developmental school, 46 rising tenth-graders between the ages of 14 and 15 were engaged from a summer science camp hosted by the researcher's university, and the remaining 14 students between the ages of 14 and 18 were involved from a summer camp program organized at a local community college. The total sample consisted of 17 fourteen-year-old, 37 fifteen-year-old, 34 sixteen-year-old, 37 seventeen-year-old, and 26 eighteen-year-old students. The mean age of all the participants was 16.18 years ($SD = 1.28$). The sample included about 60% females ($n = 90$) and 40% males ($n = 61$). The participants' self-identified ethnicity included 53.6% White ($n = 81$), 18.5% African-American ($n = 28$),

16.6% Hispanic ($n = 25$), 7.3% Asian ($n = 11$), 0.7% Native Hawaiian ($n = 1$), and 3.3% others ($n = 5$).

Measure

The Modeling Self-Efficacy survey consisted of nine modeling problems (see Appendix A). Each modeling problem was followed by four self-efficacy questions including students' confidence in understanding the problem, determining a strategy, determining the information, and correctly solving the modeling problem. Following Bandura's (2006) recommendation, students rated their confidence on a 100-point scale ranging from 0 (not at all sure) to 100 (very sure) (see Appendix B).

Procedure

Students were invited to participate in the study by providing them information about the purpose of the study, tasks involved, the benefits and risks involved in joining this study, and the confidentiality of their responses. Students who returned signed consent forms were issued alphanumeric codes to maintain anonymity. Before administering the questionnaire, the researcher highlighted the importance of reporting accurate efficacy judgments and requested students to provide their honest opinions. Participants completed the self-efficacy survey in approximately 25 minutes. It is important to note that participants did not solve any of the modeling problems. They reported their judgments for understanding and solving modeling problems after reading them. Additionally, five students from the research developmental school with different ability levels were engaged in think-aloud interviews to ascertain that students understood these problems and could solve them. These students were selected based on the recommendations of the classroom teachers.

Data Analysis

Descriptive analysis of the scale (see Table 3-1) indicated that participants' reported high levels of self-confidence in understanding and solving the Cinema Outing ($M = 87.78$, $SD = 13.84$), Library System ($M = 87.72$, $SD = 17.28$), and Children's Camp ($M = 886.48$, $SD = 12.80$) problems. They reported almost similar confidence ratings for the Hospital ($M = 85.0$, $SD = 15.92$), Holiday ($M = 84.18$, $SD = 17.30$), and Energy Needs ($M = 83.40$, $SD = 18.85$) problems. Students appeared to be least confident in solving the Course Design ($M = 81.92$, $SD = 16.40$), Irrigation ($M = 77.86$, $SD = 18.34$), and Freezer ($M = 77.85$, $SD = 20.29$) problems.

Internal consistency estimates ensure that participants' responses are consistent across items when a single form of a test is administered (Kline, 2005). It is important to have high internal consistency among the items within a scale so that all the items are consistently measuring students' self-efficacy beliefs for modeling tasks. The full scale was found to have Cronbach's alpha coefficient equal to .89. Additionally, item-total correlation analyses were performed to ensure that all the items on the scale were homogeneous. Kline (2000) suggested .30 as an acceptable corrected item-total correlation for the inclusion of an item. Item-total correlations (see Table 3-2) for the scale, ranged from .48 to .77, suggesting that all the items were adequately measuring a single underlying construct.

Factor analysis was performed to establish construct validity that also means identifying any underlying association between the items on the scale. Principal Component Analysis with varimax rotation indicated a single factor model because the first factor accounted for 54.5% of the variance in students' efficacy to understand modeling tasks in comparison to the second factor that only accounted for 9.3% of the

total variance. The scree plot showed that the second (9.3%) and third (8.5%) factors were similar in magnitude (see Figure 3-2). Further, inspection of the component matrix table showed that all items load strongly on the single underlying construct (all factor loadings were higher than .67).

Content validity measures whether the wording and format of the questions on a scale are consistent with the construct of interest. The items on the self-efficacy scale were reviewed and verified by experts in the field including researchers familiar with the psychological construct and people with measurement expertise.

Further, five students from a research developmental school with different ability levels were engaged in think-aloud interviews during which they were encouraged to verbalize the steps taken by them in solving modeling tasks. The major purpose of the think aloud interview was to ascertain whether the modeling tasks were sufficiently challenging to activate students' cognitive and metacognitive skills. Think-aloud interviews revealed that problems on the modeling test were not very challenging for tenth-grade students between 16 to 18 years of age. Accordingly, four students from lower grade-levels, specifically 8th- and 9th-grade were selected to solve the modeling problems. These students were interviewed individually and were encouraged to share their thought processes about the strategies they used in understanding and solving these problems. Since the modeling problems were found to be sufficiently challenging for eighth- and ninth-grade students, it was decided to recruit eighth- and ninth-grade students between 13 to 15 years of age for the dissertation study.

Research Design

The present study measured the degree of association between self-efficacy beliefs, self-reported use of cognitive and metacognitive strategies, and students' performance on the modeling test. Thus, this study followed a correlational research design to determine whether and to what degree the variables involved in the study were related to one another (Clark & Creswell, 2010). It is important to note that correlational research is not causal in nature. As such, no attempts were made to establish cause-effect relationships among the variables. Data were collected in the form of self-report questionnaires and students' responses on a modeling test. Structural equation modeling (SEM) techniques were used to explain relationships among the variables under investigation (Byrne, 2012; Kline, 2005/2011). SEM helps to estimate and test direct and indirect effects of the latent variables involved in a system through a series of regression equations. Latent variables, such as self-efficacy beliefs, cognitive strategies, and metacognitive strategies, are constructs that can neither be observed nor measured directly. Rather, they are indirectly measured by using observed variables that reflect different characteristics of the desired construct. For example, in this study students' use of metacognitive strategies was measured indirectly through their ratings on nine items measuring their ability to plan, monitor, and regulate goals or problem-solving strategies. The structural relationships among the variables can be represented in the form of a statistical model (see Figure 3-1).

Determination of Minimum Sample Size

Determining appropriate sample sizes for research studies is crucial to detecting statistically significant relations if they exist. Meeting the criteria for the minimum sample size decreases the probability of committing a Type II error (failing to detect relations

among the variables when they do exist) or increases the power of a study. With regard to SEM and confirmatory factor analysis, there is little consensus in the research community concerning minimum sample size requirements (Kline, 2011; Mundfrom, Shaw, & Ke, 2005). Various methods have been suggested in this regard such as a minimum sample size approach of 200 participants, estimating sample sizes by using the $N:q$ rule, where N is the number of participants and q is the number of parameters included in the statistical model, or through conducting power analysis (Jackson, 2003; Kline, 1998, 2005, 2011; Marsh, Balla, & McDonald, 1988; Mundfrom et al., 2005). In determining sample sizes through the $N:q$ rule, it is unclear how many participants (e.g., 20, 10, or 5) should be selected for each statistical variable (Kline, 2005/2011; Jackson, 2001/2003). Kline (2005/2011) suggested that sample sizes greater than 200 are large enough for statistical model testing as well as to obtain a desired level of statistical power. Following Kline's recommendations, the current study recruited 225 eighth- and ninth-graders from a local research developmental school affiliated with the researcher's university.

Method

Participants

A total of 325 eighth- and ninth-grade students in 13 classrooms were invited to participate in this study. Out of these, 236 (72.6%) students returned the signed parent consent and student assent forms. Eleven students were absent on the day the questionnaires were administered. Thus, 225 eighth- ($n = 88$, 39.11%) and ninth-grade ($n = 137$, 60.8%) students participated in the study. The average age of the participants was 14.22 with a standard deviation of 0.85. The number of female students ($n = 122$, 54.2%) was slightly higher than the number of male students ($n = 103$, 45.8%).

Participants reported their ethnicity as White ($n = 111$, 49.3%), African American ($n = 46$, 20.44%), Hispanic ($n = 33$, 14.6%), Asian ($n = 12$, 5.33%), and Native Hawaiian ($n = 1$, 0.44%). The remaining students reflected their ethnic background as either a combination of these categories ($n = 19$, 8.4%) or as “others” ($n = 3$, 1.33%).

Measures

Three instruments were used to measure the desired constructs including: (1) a self-efficacy scale developed to measure students’ efficacy judgments on the modeling tasks, (2) a modified version of the MSLQ as developed for Connected Classroom in Promoting Mathematics (CCMS) project and used by Kaya (2007) to assess students’ use of cognitive and metacognitive strategies, and (3) a modeling test adapted from PISA 2003 problem-solving items to measure students’ modeling outcomes.

Self-efficacy scale

The self-efficacy scale assessed students’ confidence in solving modeling problems. Students provided judgments of their perceived capability to correctly solve modeling problems after reading each problem on the test. Specifically, they responded to four questions that elicited students’ self-efficacy judgments including,

1. How sure are you that you can understand this mathematical problem?
2. How sure are you that you can determine a strategy to solve this problem?
3. How sure are you that you can determine the information required to solve this problem?
4. How sure are you that you can solve this mathematical problem correctly?

Students recorded the strength of their efficacy beliefs on a 100-point scale, divided into 10-unit intervals ranging from 0 (not at all sure) to 100 (very sure) (see Appendix B).

Psychometric properties of the Modeling Self-Efficacy scale tested during the pilot study suggest that the scale has high internal consistency ($\alpha = .89$).

Motivated Strategies for the Learning Questionnaire (MSLQ)

The MSLQ is a self-report instrument designed to measure college students' motivational orientation and their use of learning strategies in studying material for a college course (Pintrich et al., 1991; Pintrich et al., 1993). The motivation and learning strategies section together represent 15 subscales (or constructs) with a total of 81 items. The present study used four subscales from the learning strategies section addressing students' use of cognitive and metacognitive strategies including elaboration, organization, critical thinking, and metacognitive self-regulation. Students reported their cognitive and metacognitive strategy use on a seven-point Likert scale from 1 representing "not at all true of me" to 7 representing "very true of me". Higher scores indicate greater levels of the constructs being measured or greater reported strategy use. The MSLQ is a widely used questionnaire that has been validated by a variety of empirical studies. Pintrich and his colleagues (1991) claim that the MSLQ scales can be used collectively as well as independently.

Since the original MSLQ instrument was developed for college students, the present study used a version of the questionnaire that was modified for the CCMS project and used by Kaya (2007). Modifications in this questionnaire were made to meet the cognitive levels of middle-grade students. Also, some items were reworded to reflect motivational beliefs and use of learning strategies in reference to mathematics. The modified questionnaire included 67 items related to student motivation, cognitive and metacognitive strategy use, and management strategies (Kaya, 2007). Because the present study focused on students' use of cognitive and metacognitive strategies, 15 items related to cognitive strategy use and 9 items concerned with metacognitive strategy use were included in the self-report questionnaire (see Appendix C). Kaya

(2007) administered the modified MSLQ to 1,626 Algebra I students to test the internal consistency of the scale and the reliability estimates indicated high item-total correlations. The elaboration (6 items, $\alpha = .78$), organization (4 items, $\alpha = .73$), critical thinking (5 items, $\alpha = .76$), and metacognitive self-regulation (9 items, $\alpha = .83$) subscales had satisfactory Cronbach's alpha values. Further, three problematic items on the original metacognitive self-regulation subscale of the MSLQ were deleted (Kaya, 2007).

Cognitive strategies. The cognitive strategies section includes 15 items across three subscales including elaboration, organization, and critical thinking (Kaya, 2007) (see Table 3-3). The elaboration subscale is designed to assess students' use of learning strategies such as paraphrasing, summarizing, and note taking. These strategies support learners to process information more deeply through translating new information into their own words and creating mental models of a problem by associating the information given in a problem to their existing knowledge (Ormrod, 2008). Students' use of elaborative strategies was measured through six items (e.g., I try to relate ideas in this subject to those in other courses whenever possible). Elaboration strategies may be helpful in solving all three types of problems chosen for the PISA problem-solving assessment. Relating the problem-solving situations to what students already know may help them to solve decision-making, system analysis and design, and troubleshooting problems.

The organization subscale consisting of four items measured the extent to which students use learning strategies such as clustering, outlining, and selecting main ideas to differentiate relevant and irrelevant information (e.g., I make simple charts, diagrams,

or tables to help me organize course material). These strategies may be useful in solving decision-making tasks that require students to identify the relevant alternatives and constraints. Organization strategies may also be helpful in solving system analysis and design problems, where students represent relationships among different parts of a system in the form of a table or a chart.

Finally, the critical thinking subscale includes five items that measured the degree to which learners apply their prior knowledge and skills to thinking logically about new situations (e.g., I treat the course material as a starting point and try to develop my own ideas about it). Critical thinking skills are considered to be the most important skills for solving modeling tasks as these strategies support learners to think analytically, consider alternative conceptions of a problem, make effective decisions, reason deductively as well as justify their reasoning.

Metacognitive strategies. The metacognitive self-regulation subscale consisting of nine items measured the extent to which students (1) plan their goals or activities (e.g., Before I study new material thoroughly, I often skim it to see how it is organized), (2) monitor their actions to enhance attention and to self-evaluate their progress (e.g., I ask myself questions to make sure I understand the material I have been studying in this class), and (3) regulate their cognitive strategies and goals (e.g., When studying for this course I try to determine which concepts I don't understand well). Items included on the metacognitive self-regulation scale are provided in Table 3-4. Prominent researchers in the field of mathematical modeling reported that metacognitive strategies such as planning, monitoring, and regulating strategies support students in self-evaluating the effectiveness of their models, creating revised models, and describing

situations using models (Blum, 2011; Magiera & Zawojewski, 2011; Lesh, Lester & Hjalmarson, 2003).

The modeling test

The third instrument used in this study was a test composed of six real-world situations to examine students' modeling success competence (see Appendix D). The modeling test was developed by adapting problems from the PISA 2003 problem-solving assessment (OECD, 2004). These problems were selected because researchers in the field of mathematical modeling often regard PISA problems as complex modeling tasks (Blum, 2011; Carriera, Amado, & Lecoq, 2011; MaaB & Gurlitt, 2011; Mousoulides, 2007; Mousoulides, Christou, & Sriraman, 2008). The PISA 2003 problems have been empirically examined and validated with students from 41 countries and the overall reliability of the problem-solving scale from which these items were adapted was very high ($\alpha = .87$). The modeling test assessed students' modeling performance through three different types of tasks: decision-making, system analysis and design, and troubleshooting. It included six modeling problems, with two problems for each type of task.

The problem-solving (or modeling) processes involved in solving decision-making, system analysis and design, and troubleshooting tasks include understanding the problem, characterizing the problem, representing the problem, solving the problem, reflecting on the solution, and communicating the solution (see Figure 3-3).

Understanding the problem is very similar to the description process of the modeling cycle. It involves making sense of the context and information given in the problem (e.g., text, diagrams, formulas, or the tabular data) by utilizing prior knowledge and experiences. Characterizing includes identifying relevant variables involved in the

problem and noticing relationships between them. It also includes “constructing hypotheses; and retrieving, organizing, considering, and critically evaluating contextual information” (OECD, 2004, p. 27). Further, learners establish relationships between the variables by representing the situation in tabular, graphical, symbolic, or verbal forms. In order to successfully solve these problems, students need to make predictions about real-world problems. This includes making appropriate decisions in the case of decision-making tasks, analyzing or designing systems in the case of system analysis and design tasks, and diagnosing faulty systems in the case of troubleshooting tasks. Verification involves evaluating results within the context of the real-world situation (OECD, 2004). Finally, communication involves selecting effective methods of communication to report solutions such as choosing appropriate forms of media and representations.

The decision-making tasks measured the extent to which students could make appropriate decisions by choosing strategically among several alternatives provided under a given set of conditions. The decision-making skills were tested through Cinema Outing and Energy Needs (see Appendix D) problems. These problems involved a variety of information, and students were required to understand and provide solutions to these problems by identifying the constraints given in the situation, translating the information into meaningful representations, and making a decision after systematically considering all the alternatives and constraints (OECD, 2004). For example, the Energy Needs problem required students to select suitable food for a person after calculating his/her required daily energy needs. In order to calculate the energy needs of a person, students needed to integrate two or more pieces of information such as age, gender,

activity level, and occupation of a person. Students' ability to make accurate decisions is largely affected by the number of factors present in a problem, especially in separating the relevant from the irrelevant information.

The system analysis and design tasks required students to identify complex relationships among the variables or to design a system by satisfying all the conditions given in a problem. The two system analysis and design problems included in the test were Children's Camp and Course Design (see Appendix D). Similar to decision-making tasks, system-analysis and design problems involved a variety of information and students needed to sort through the information in order to depict relationships among the variables. But unlike decision-making problems, all the alternatives were not given and the constraints were not obvious. For example, the Children's Camp problem involved assignment of children and teachers into different dormitories by matching the capacity of each dorm with the number and gender of the people. It required thorough understanding of the context of the situation, list of adults and children, and knowledge of the dormitory rules. As such, these problems required students to think logically and critically about all the variables as well as constantly monitor, reflect, and adjust their actions.

The third type of task, troubleshooting problems, required students to diagnose, rectify, and improve a faulty or underperforming system. The modeling test included two trouble-shooting problems, Irrigation and Freezer (see Appendix D). In order to solve these problems, students needed to understand the main components of a system as well as the role of each component in the system's functioning. Additionally, they were required to understand how different components of a system interact with each other

causally (OECD, 2004). Based on this understanding, students were required to diagnose a malfunction of a system and propose an appropriate solution. Students could communicate their recommendations by either drawing a diagram or writing a problem solution report. For example, the Freezer problem was a trouble-shooting item, where students needed to diagnose the probable cause of a malfunctioning freezer based on several variables such as the knowledge of the manual, the functioning of the warning light, the state of the temperature control, and external indications about the freezer motor. It is important to note that all six problems on the modeling test were either open-ended having more than one correct solution or in multiple-choice format requiring them to choose “yes” or “no” for a series of questions.

Procedure

Data Collection

The present study was conducted during the fall of 2012 at a developmental research school. Students were recruited following the approval of procedures from the University of Florida Institutional Review Board. All the students completed the MSLQ questionnaire as well as solved modeling problems after rating their confidence for solving these problems. Both the questionnaires and modeling test were administered during regular class periods in two sittings. The MSLQ survey took approximately 10-15 minutes to complete. Before the administration of the questionnaire, students were instructed to respond to the items with reference to their mathematics classroom. Students took approximately 15 minutes in rating their confidence in solving modeling tasks. Finally, they solved problems on the modeling test in approximately 30 minutes. During the modeling test administration, students were encouraged to not only solve but also to provide justifications for their responses. The present study, however, did not

take into account students' justifications while scoring their responses on the modeling test.

Data Analysis

Scoring scheme

Students' performance on the modeling test was evaluated in accordance with the scoring system used in the PISA 2003 problem-solving assessment (see Appendix E). Students could earn a maximum of 2 points for some problems (e.g., Cinema Outing, Energy Needs, Children's Camp, and Course Design), while other problems (e.g., Irrigation, Freezer) were worth a maximum of 1 point. As such, they could earn a maximum of 10 points on the modeling test. The Cinema Outing problem required students to identify movies that three friends could watch together upon analyzing the duration and show times for each movie. Students received a maximum score of 2 for correctly choosing "yes" or "no" for all the six multiple-choice questions, and a partial score of 1 for answering all but one of the questions correctly. They received zero points for incorrectly answering more than two multiple-choice questions.

The Energy Needs problem required students to suggest a suitable food for a person that aligns with his or her energy needs. To receive full credit, students needed to show all the calculations including the total energy of the fixed price menu, sum of the fixed price menu and the person's energy intake for the day, and difference between this sum and the person's recommended daily energy needs followed with a correct conclusion. Students received partial credit in two ways, either by showing all the calculations correctly but providing a wrong conclusion, or making a minor error in one of the calculations steps leading to a wrong conclusion. Students, however, did not get any credit for simply calculating total energy of the fixed price meal.

The Children's Camp was an open-ended problem involving assignment of adults and students to different dormitories based on the dormitory rules. A full credit response involved allocating people to eight dormitories after ensuring the total number of girls (e.g., 26), boys (e.g., 20), and adults (e.g., 4 females and 4 males) were equal to the required number. Further, the total number of people in each dormitory should not exceed the number of beds, adults and children in each dormitory should be of the same gender, and there should be at least one adult sleeping in each dormitory. Students received a partial credit of 1 point if they violated at most two of the recommended six conditions. They did not receive any credit for violating more than two conditions.

The Course Design problem required students to sequence 12 college courses over a three-year period. Full credit involved listing subjects by satisfying the two recommended conditions. Students received partial credit of 1 point if they listed all the subjects in proper order except mechanics and economics. However, they received no credit for completing the whole table correctly but failing to put electronics courses (e.g., Electronics (I) and Electronics (II)) into the table. The Irrigation problem required students to decide whether the water would flow through all the way by choosing "yes" or "no" in three different problem situations. Students earned a full credit of 1 point on correctly answering all the three multiple-choice questions. Unlike other problems, they could not earn any partial credit for this problem. The Freezer is a multiple-choice problem that required students to detect whether the warning light of a malfunctioning home freezer was working properly when the temperature was controlled at different positions. In order to receive full credit, students needed to answer all three questions

correctly. Similar to the Irrigation problem, no partial credit was given if any of the three responses were incorrect.

Scoring procedure

The researcher and a fellow mathematics education graduate student scored participants' responses on the modeling test. Interrater agreement was examined between the two raters to ensure the consistency of the implementation of the scoring rubric. It represents the "extent to which different judges tend to make exactly the same judgment about the rated subject" (Tinsley & Weiss, 2000, p. 99). Interrater agreement was reported by measuring Cohen's kappa and values higher than .80 are generally considered to be acceptable (Tinsley & Weiss, 2000). The present study found high interrater agreement between the two raters ($\kappa = .96$).

Descriptive analysis

Descriptive analysis was conducted by reporting reliability estimates, patterns of missingness, and descriptive statistics for each construct. The reliability estimates for elaboration, organization, critical thinking, metacognitive self-regulation subscales as well as self-efficacy and modeling test were determined by calculating Cronbach's alpha. Coefficient alpha measures internal consistency of a scale that refers to the "degree to which responses are consistent across the items within a single measure" (Kline, 2005, p.59). In the social sciences, acceptable reliability estimates range from .70 to .80 (Kline, 2005). Missing values analysis procedure including pattern of missing data was performed using the SPSS statistical software. Specifically, univariate descriptive statistics including non-missing values, means, standard deviations, and number and percent of missing values were computed.

Descriptive statistics including mean scores for each subscale in the MSLQ and mean self-efficacy scores for each modeling problem were calculated. By following the recommendations made in the MSLQ manual, mean scores for the elaboration, organization, critical thinking, and metacognitive self-regulation subscales were calculated by averaging participants' ratings across all the items within that subscale. Further, participants' mean self-efficacy scores for the six modeling problems were calculated by averaging participants' ratings across the four self-efficacy questions (i.e., confidence in understanding the problem, determining information, determining strategies, and solving the problem).

Further, construct validity for the MSLQ and Modeling Self-Efficacy scale was examined through Confirmatory Factor Analysis (CFA). In CFA, relationships between the observed indicators and underlying latent constructs, known as factor loadings, are specified a priori based on the review of the literature (Byrne, 2012). The hypothesized model is tested by examining goodness-of-fit indices such as, Chi-square test statistics, comparative fit index (CFI), Tucker Lewis index (TLI), and root mean square error of approximation (RMSEA). In the present study, the CFA of the MSLQ was conducted by allowing elaboration, organization, critical thinking, and metacognitive self-regulation items to load freely on their corresponding latent factors. The CFA of the Modeling Self-Efficacy scale was performed by loading participants' mean self-efficacy scores for each of the six modeling problems on the overall modeling self-efficacy latent variable.

Analyses

Data were analyzed using SEM techniques. The statistical calculations such as estimating fit indices, errors, and model parameters were performed using the Mplus version 7 program. The hypothesized statistical model was tested using weighted least

square means and variance adjusted (WLSMV) estimator. This estimator was selected because it produces accurate parameter estimates and unbiased standard errors with varying sample sizes ($N = 100$ to $1,000$) and models in which observed variables are measured on widely varying scales (Brown, 2006; Muthèn & Muthèn, 1998-2012). It also provides superior measurement model fit and more precise factor loadings with categorical data.

SEM is a useful methodology to study relations among observed and unobserved (i.e., latent) variables in both experimental and non-experimental settings (Byrne, 2009/2012; Hoyle, 1995). Such relations, however, are not causal in nature (Kline, 2005). These relations can be represented in the form of a series of structural equations as well as depicted pictorially in the form of a structural model (Byrne, 2012). The hypothesized structural model that guided the present study is presented in Figure 3-1. Students' use of cognitive strategies was measured indirectly through their self-reported use of elaboration, organization, and critical thinking strategies. Thus, students' mean ratings for the elaboration, organization, and critical thinking subscales were loaded on the cognitive strategy latent variable. Students' use of metacognitive strategies was measured indirectly through their ratings on nine items measuring their self-reported use of planning, monitoring, and regulating strategies. It is important to note that mean of students' ratings across nine metacognitive items was not computed rather students' ratings for each metacognitive item were loaded on the overall metacognitive latent variable. Students' self-efficacy beliefs for modeling tasks were indirectly measured in terms of their confidence in solving decision-making, system analysis and design, and troubleshooting tasks. Self-efficacy beliefs for decision-making, system analysis and

design, and troubleshoot tasks were calculated by computing students' mean ratings for the Cinema Outing and Energy Needs, Children's Camp and Course Design, and Irrigation and Freezer problems, respectively. Modeling outcomes were indirectly measured through students' success in solving decision-making, system analysis and design, and troubleshooting tasks. Modeling success rates for decision-making, system analysis and design, and troubleshooting tasks were calculated by averaging students' scores in Cinema Outing and Energy Needs, Children's Camp and Course Design, and Irrigation and Freezer problems, respectively.

SEM determines the extent to which the hypothesized model fits with a set of data obtained from a given sample. The general structural equation model consists of two sub models: a measurement model and a structural model (Byrnes, 2012; Hoyle, 1995; Kline, 2005). The measurement model determines how well the latent variables are described by the observed variables. This model is analogous to confirmatory factor analysis because it indicates how each observed measure (e.g., items or subscales on the questionnaire) loads on a particular factor (i.e. latent variable). The second component is the structural model, which defines relations among the unobserved latent variables and the extent to which each latent variable "directly or indirectly influence(s) changes in the values of certain other latent variables in the model" (Byrne, 2012, p.14). In the present study, the structural model describes relationships between modeling self-efficacy beliefs (exogenous latent variable) and cognitive strategies, metacognitive strategies, and modeling tasks (endogenous latent variables).

Benefits of SEM. There are several benefits of using SEM over multivariate procedures, such as Analysis of Variance (ANOVA) and multiple regressions (Byrne,

2012). First, SEM involves a confirmatory approach to the data analysis because relations among the variables are specified a priori based on the review of the literature. Second, SEM provides explicit estimates for the measurement errors, which are not assessed correctly using traditional multivariate procedures. Measurement errors are associated with observed variables, and accounting for such errors results in accurate estimation of the structural relations between the observed and latent variables. Third, SEM allows researchers to test several hypotheses and make inferences based on both latent and observed variables.

Five basic steps of SEM. SEM involves five basic steps including model specification, model identification, model estimation, model testing, and model modification (Hoyle, 1995). Model specification involves proposing a model by reviewing relevant theory and literature (e.g., Figure 3-1). Specifically, it includes establishing observed variables that can appropriately measure the latent variables as well as defining relations between observed and latent variables.

Model identification focuses on whether “a single, unique value for each and every free parameter can be obtained from the observed data” (Hoyle, 1995, p. 4). A model is said to be identified if it meets two basic assumptions: “(1) there must be at least as many observations as free model parameters ($df_M \geq 0$), and (2) every unobserved (latent) variable must be assigned a scale (metric)” (Kline, 2005, p. 105). Structural models may be under-identified, just-identified, or over-identified. If the number of free parameters exceeds the number of observations, a model is said to be under-identified and cannot be estimated. A just-identified model fits the data perfectly, as it involves only one possible set of values for the parameters. In general, over-

identified models, in which the number of observations is more than the number of independent parameters, are preferred as they facilitate statistical model testing.

The model estimation process yields parameter values such that the “discrepancy (i.e., residual) between the sample covariance matrix and the population covariance matrix implied by the model is minimal” (Byrne, 2012, p. 65). Specifically, during this stage initial values are plugged in for all the parameters and then the model is estimated iteratively using an estimator, such as WLSMV, until the discrepancy between sample and population covariance matrix is minimum. This is also known as model convergence.

The model-fit test is one of the most crucial steps of SEM since it assesses the extent to which the observed data fit the proposed statistical model. SEM allows researchers to test theoretical propositions by determining the goodness-of-fit between the hypothesized statistical model and the data collected from the population of interest. Byrne (2012) describes the model-fitting procedure in SEM as follows:

$$\text{Data} = \text{Model} + \text{Residual}$$

In this equation, “data” symbolizes scores obtained from the sample on the observed variables, “model” represents the proposed statistical model denoting relations between the observed and latent variables, and if possible relations between latent variables as well. This model is generally hypothesized after the review of extant literature.

“Residual” represents the difference between the hypothesized model and the observed data. As such, goodness-of-fit is the variance in the data that is not explained by the proposed model.

The model-fit is generally evaluated based on two broad criteria: (1) the goodness-of-fit statistic and (2) the individual parameter estimate (Byrnes, 2012). Byrnes further recommends that the model should be examined based on several criteria. Some prominent goodness-of-fit statistics that indicate overall fit of the model include chi-square test of model fit (χ^2), the root mean square error of approximation (RMSEA), the comparative fit index (CFI), and the Tucker Lewis index (TLI).

The chi-square index evaluates the discrepancy between the population covariance matrix and the sample covariance matrix. This means as the chi-square values increases, the fit of the model becomes worse. The null hypothesis in a chi-square goodness-of-fit test states that the hypothesized model fits the data. In other words, factor loadings, factor variances and covariances, and residual variance for the model under study are valid (Byrne, 2012). *Mplus* typically calculates this statistic as NF_{\min} , where N represents the sample size and F_{\min} is the minimum fit function (Byrne, 2012). The probability value associated with χ^2 determines the fitness between the hypothesized model and the model obtained from the sample population. It represents the likelihood that the chi-square test statistic is greater than the χ^2 value when the null hypothesis is true. Thus, higher p-values ($p > .05$) indicate closer fitness between the two types of models. It is important to note, however, that chi-square's sensitivity to large sample sizes frequently results in rejection of the hypothesized model. The effect of large sample sizes can be reduced by dividing the chi-square index by the degrees of freedom (Kline, 2005). Higher correlations among observed variables also increase the probability of rejecting the null hypothesis (Miles & Shevlin, 2007). This occurs because higher correlations among the variables give greater power to the tested model causing

an increase in chi-square index. It is, therefore, recommended to check the results obtained from chi-square with other fit-indices such as CFI, TLI, or RMSEA.

Both CFI and TLI are incremental indices of fit in SEM, which measure the relative improvement in fit of the hypothesized model in comparison to the baseline model (Byrne, 2012). The baseline model is also called the null or independence model that assumes zero covariance among the observed variables (Kline, 2005). The values of CFI lie between .0 and 1.0, with values greater than .95 indicating that the population matrix fits closely with the hypothesized model (Byrne, 2012). TLI is called the nonnormed index since its values lie beyond the normal range of .0 to 1.0. Similar to CFI, TLI values close to .95 indicate that the hypothesized model is a good-fitting model.

RMSEA tells us how well the model with “unknown but optimally chosen parameter estimates would fit the population covariance matrix” (Browne & Cudeck as cited in Byrne, 2012). It assumes that the model does not fit the sample data perfectly. Unlike chi-square, it is not sensitive to large sample sizes. RMSEA values less than .05 are considered a good fit, values in the range of .06 and .08 are considered a moderate fit, and values greater than .10 indicate poor fit.

The goodness-of-fit statistics evaluate model fitness by concentrating on the model as a whole. On the other hand, the individual parameter estimates focus on “appropriateness of the estimates and their statistical significance” (Byrnes, 2012, p. 77). Specifically, parameter estimates assess the degree to which statistical estimates are consistent with the proposed model, such as correct sign and size. Values of the estimated parameters that fall beyond the required range, such as correlations greater

than 1.00 or negative variances, represent incorrect estimates. The estimated standard errors with extremely large and small values also indicate poor model fit.

Model modification generally occurs when the original model does not fit the data as indicated by the goodness-of-fit indices. It involves adding or removing statistical paths as suggested by the residuals and modification indices (MI) obtained from running the original model (Hoyle, 1995). Byrne further specified that statistical paths in the proposed model should not be modified solely on the basis of modification indices, the suggested paths should also be theoretically appropriate.

Assumptions of SEM. There are two basic assumptions of structural equation modeling: independence assumption and multivariate normality assumption. The independence assumption implies that “error in predicting Y from X for one case is unrelated to that of another case” (Kline, 2005, p. 23). The independence assumption requires independent observations obtained through random sampling. This assumption is usually violated in social and behavioral sciences because most often participants are nested within schools or classrooms or they are not selected through random sampling. Nonrandom sampling does not provide accurate estimates of variances and covariances associated with the latent constructs (McDonald & Ho, 2002). In the present study, the independence assumption was violated because students belonged to different classrooms within a school, and they were selected through nonrandom sampling. Fabrigar, Wegener, MacCallum, and Strahan (1999) suggested that in the case of convenience sampling, researchers should refrain from selecting participants who are relatively homogeneous with respect to the factors of interest. In the present study, the impact of this assumption violation was reduced to some extent because the

selected students belonged to varying socioeconomic status and different cultural backgrounds.

Multivariate normality means that observations are drawn from a continuous and multivariate normal population (Kline, 2005). The violation of this assumption results in substantial overestimation of goodness-of-fit statistics (e.g., χ^2 , CFI, TLI, RMSEA) and underestimation of standard error estimates. Although the measurement model in the present study was tested using the WLSMV estimator, which produces accurate parameter estimates under non-normality, the multivariate normality assumption was tested by computing univariate skewness and kurtosis values for each variable. Both skew and kurtosis describe the distribution of observed data around the mean. Skewness indicates whether the observed scores are above (negative skew) or below the mean (positive skew) (Kline, 2005). On the other hand, kurtosis values suggest whether the multivariate distribution of the observed variables has high peak and heavier tails (positive kurtosis) or the curve is flat with light tails (negative kurtosis). Further, it is important to note that skew values influence tests of means, whereas kurtosis values impact tests of variance and covariance (DeCarlo, 1997 as cited in Byrne, 2012). Considering the fact that SEM is based on analysis of covariance structure, parameter estimates and standard errors tend to be more influenced by abnormal kurtosis values in comparison to skew values. Kline (2005) reported that skewness greater than 3.0 generally suggests a serious problem. Kurtosis values greater than 10.0 might be interpreted as a sign of a problem while the values greater than 20.0 may point to a serious problem. These reports were used as a point of reference for the examination of the multivariate normality of the current data.

Handling Missing Data. Missing data causes problems for researchers using SEM techniques. Choosing the most appropriate method for handling missing data is of utmost importance because applying inappropriate methods may lead to bias in standard errors and test statistics (Allison, 2003). According to Widaman (2006), the cause of missing data can be due to item nonresponse, scale nonresponse, or dropout of the participants during the course of a study. Item nonresponse may occur when a participant does not respond to a particular item because of temporary lack of attention, inability to comprehend a situation, or personal issues. Scale nonresponse occurs when a participant fails to respond to all the items pertinent to a particular construct (e.g., if a participant does not respond to all six items of the elaboration scale).

Further, missing data are classified either as missing completely at random (MCAR) or missing at random (MAR) (Kline, 2005; Widaman, 2006). MCAR means that the missingness is completely random and is not predictable from either the observed variables or latent variables in the study. The missing data were tested for MCAR assumption by using Little's MCAR test. The null hypothesis for Little's MCAR test assumes that data are missing completely at random. Hence, p-values less than .05 significance level indicates data are not missing completely at random. MAR means that the missingness is unpredictable from the latent variables as well as the observed variable for which it is a missing data indicator. However, it is predictable from other observed variables.

Some common techniques to handle missing data include listwise deletion, pairwise deletion, mean imputation, and Maximum Likelihood (ML) estimation (Enders & Bandalos, 2001). Listwise deletion methods remove the complete record of a participant

with any missing values. Although this method is very easy to implement, it results in the loss of valuable data leading to small sample size that further decreases power and accuracy, and biased parameter estimates when the data are not MCAR (Arbuckle, 1996; Wothke, 2000). Nevertheless, it is recommended to use listwise deletion if the percentage of observations that contain missing values is reasonably low (less than 5%) (Bentler, 2005; Hair, Black, Babin, Anderson, & Tatham, 2006).

The second method to handle missing data involves pairwise deletion. In this method, cases are excluded only when the case has missing data for a variable that is part of the data analysis. Similar to listwise deletion, it is easy to apply and results in less loss of data but has several disadvantages. First, the pairwise deleted correlation matrix may not be positive, which means certain mathematical operations with the matrix will be difficult to carry out. Second, it results in biased parameter estimates when the data are not MCAR. Third, pairwise deletion raises the tendency to reject the statistical model (Enders, 2001). Fourth, it produces standard error estimates that may not be consistent with true standard errors. This problem arises because it uses different sample sizes for estimating different parameters.

Another way of handling missing data is mean imputation, which involves substituting missing values with the mean score of that observed variable. Imputation allows researchers to include subjects with missing values in data analysis, but it distorts the shape of the distribution of the data as well as relationships between variables. It also results in reduced variance and underestimated standard errors. In general, this method is not an appropriate method to handle missing data.

In comparison to these methods, maximum likelihood (ML) estimation has been regarded as one of the most promising methods to handle missing values in SEM because it can handle missing data under the MAR assumption (Byrne, 2012; Kline, 2005). Unlike mean imputation and listwise deletion, ML neither fills in the missing values nor discards the data. Rather, it uses all the available data to produce parameter estimates that “have the highest probability of producing the sample data” (Baraldi & Enders, 2010). Specifically, it identifies population parameter values and by using a log likelihood function generates sample estimates that best fit the data. Further, Byrne (2012) indicated several benefits of using this method. First, in comparison to listwise and pairwise estimates, ML estimation provides more reliable and efficient solutions under MCAR assumption. Second, ML offers reliable estimates even when the data values are missing under MAR conditions. Third, ML estimation does not cause any problems with the covariance matrices that occur during the case of pairwise deletion. In order to use the ML estimation method to handle missing data, several conditions must be satisfied including existence of a valid model, large sample size, multivariate normal distribution for observed variables, and use of a continuous scale for the observed variables (Byrne, 2001). The most challenging assumption in the present study would be the treatment of ordinal scale variables (e.g., Likert-scale) as continuous. Byrne (2001) suggested that the violation of this assumption can be handled if the observed variables have multivariate normal distribution and include four or more categories. As discussed before, unless extreme values for skewness and kurtosis are detected, ML methods provide reliable estimation.

Multicollinearity. Multicollinearity is yet another serious issue influencing SEM analyses. It occurs when there exist high inter-correlations among the latent variables causing the dependent variable to load on more than one factor. It is problematic because it produces singular covariance matrices and makes some mathematical calculations difficult to carry out (Kline, 2005). In the present study, multicollinearity between the latent variables was reported using the correlation matrix with correlations greater than .90 indicating multicollinearity.

Direct and Indirect Effects. Direct effects between the exogenous (e.g., self-efficacy beliefs) and endogenous variables (e.g., cognitive strategies, metacognitive strategies, and students' modeling outcomes) are interpreted as path coefficients or regression coefficients (Kline, 2005). Indirect effects involve "one or more intervening variables presumed to 'transmit' some of the causal effects of prior variables onto subsequent variables" (Kline, 2005, p. 68). Intervening variables that explain a relationship between two variables are also known as mediators. Similar to direct effects, indirect effects of the variables are also interpreted as path coefficients. Indirect effects are generally estimated as the product of two path coefficients. For example, the basic mediation model as shown in Figure 3-4 consists of three variables, the independent or the exogenous variable X , the dependent or the endogenous variable Y , and the mediator M . If 'a' is the coefficient for X in a model predicting M from X , 'b' and 'c' are the coefficients in a model predicting Y from M and X respectively (see Figure 3-4), then 'c' denotes the direct effect of X on Y and the product of 'a' and 'b' quantifies the indirect effect of X on Y through M . The total effect is equal to the sum of the direct effect of X on Y and the indirect effect through the mediating variable M . Additionally, it

is important to note that an independent variable (X) can indirectly influence a dependent variable (Y) through a mediating variable (M) even if X and Y are not correlated (Mathieu & Taylor, 2006).

Although there are several methods available (e.g., Sobel test, bootstrapping, and the empirical M -test) to test the statistical significance of the mediating variables, researchers (e.g., MacKinnon, Lockwood, & Williams, 2004; Preacher & Hayes, 2004; Shrout & Brogler, 2002) now advocate using bootstrapping procedures for several reasons. First, bootstrapping is already implemented in some SEM software such as Mplus. Second, unlike the Sobel test, it does not assume normality of the sampling distribution of the indirect effect (Preacher, Rucker, & Hayes, 2007). Third, unlike M -test, it can be used to test the effect of the mediating variables in complex path models (William & Mackinnon, 2008). Fourth, it provides better estimates in small to moderate samples. In bootstrapping method, samples are drawn with replacement from the population of interest. Then, the indirect effect is estimated for each resampled data set. This process is repeated for k (e.g., 1000) number of times, which on completion provides k estimates of the indirect effect. The distribution of these k estimates serves as the empirical approximation of the sampling distribution of the indirect effects. Bootstrapped standard errors and confidence intervals for the indirect effects are calculated using this distribution. In Mplus, bootstrapped standard errors and confidence intervals for the indirect effects can be requested by specifying the number of bootstrap draws to be used in the computation.

Assumptions of the Study

The study holds three assumptions. First, students engaged in this study would make accurate self-efficacy judgments for modeling tasks. Second, students would

express their true feelings and provide honest reports about their use of cognitive and metacognitive strategies during academic learning. Further, students' self-efficacy judgments and their responses on the self-report questionnaire would not be affected by any social or peer pressure. Third, students would expend a lot of effort in solving modeling tasks.

Table 3-1. Item statistics for the Modeling Self-Efficacy scale

	<i>N</i>	Mean	Standard Deviation
SE1	150	87.78	13.84
SE2	150	83.40	18.85
SE3	150	84.18	17.30
SE4	150	86.48	12.80
SE5	150	81.91	16.40
SE6	150	87.71	17.27
SE7	150	77.87	18.34
SE8	150	77.85	20.29
SE9	150	85.05	15.92

Note. SE1 = Cinema Outing, SE2 = Energy Needs, SE3 = Holiday, SE4 = Children's Camp, SE5 = Course Design, SE6 = Library System, SE7 = Irrigation, SE8 = Freezer, SE9 = Hospital.

Table 3-2. Item-Total Correlation Analysis

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
SE1	664.47	9923.79	.773	.691	.868
SE2	668.85	9722.87	.583	.410	.881
SE3	668.06	10262.51	.480	.279	.889
SE4	665.76	10362.06	.660	.497	.876
SE5	670.33	9732.35	.693	.540	.871
SE6	664.53	9783.92	.633	.533	.876
SE7	674.38	9533.13	.633	.478	.874
SE8	674.40	9219.43	.671	.510	.874
SE9	667.20	9759.22	.709	.560	.870

Note. SE1 = Cinema Outing, SE2 = Energy Needs, SE3 = Holiday, SE4 = Children's Camp, SE5 = Course Design, SE6 = Library System, SE7 = Irrigation, SE8 = Freezer, SE9 = Hospital.

Table 3-3. Items for cognitive strategies with three scales

Scales	
Elaboration	
1.	When reading (your mathematics textbook) for this class, I try to relate the material to what I already know.
2.	I try to understand the material in this class by making connections between the readings (your mathematics textbook) and the concepts from my teachers' lectures.
3.	I try to apply ideas from course readings (your mathematics textbook) in other class activities such as lecture and discussion.
4.	When I study for this class, I pull together information from different sources, such as lectures, readings, and discussions.
5.	I try to relate ideas in this subject to those in other courses whenever possible.
6.	When I study for this course, I write brief summaries of the main ideas from the readings (your mathematics textbook) and my class notes.
Organization	
1.	When I study the readings (your mathematics textbook) for this course, I outline the material to help me organize my thoughts.
2.	When I study for this course, I go through the readings (your mathematics textbook) and my class notes and try to find the most important ideas.
3.	I make simple charts, diagrams, or tables to help me organize course material.
4.	When I study for this course, I go over my class notes and make an outline of important concepts.
Critical Thinking	
1.	I often find myself questioning things I hear or read in this course to decide if I find them convincing.
2.	When a theory, interpretation, or conclusion is presented in class or in the readings, I try to decide if there is good supporting evidence.
3.	I treat the course material as a starting point and try to develop my own ideas about it.
4.	I try to play around with ideas of my own related to what I am learning in this course.
5.	Whenever I read or hear an assertion or conclusion in this class, I think about possible alternatives.

Table 3-4. Items for metacognitive strategies scale

Metacognitive Self-regulation	
1.	When I become confused about something I'm reading for this class, I go back and try to it out.
2.	If course readings are difficult to understand, I change the way I read the material.
3.	Before I study new course material thoroughly, I often skim it to see how it is organized.
4.	I ask myself questions to make sure I understand the material I have been studying in this class.
5.	I try to change the way I study in order to fit the course requirements and the way my teacher presents the material.
6.	I try to think through a topic and decide what I am supposed to learn from it rather than just reading it over when studying for this course.
7.	When studying for this course I try to determine which concepts I don't understand well.
8.	When I study for this class, I set goals for myself in order to direct my activities in each study period.
9.	If I get confused taking notes in class, I make sure I sort it out afterwards.

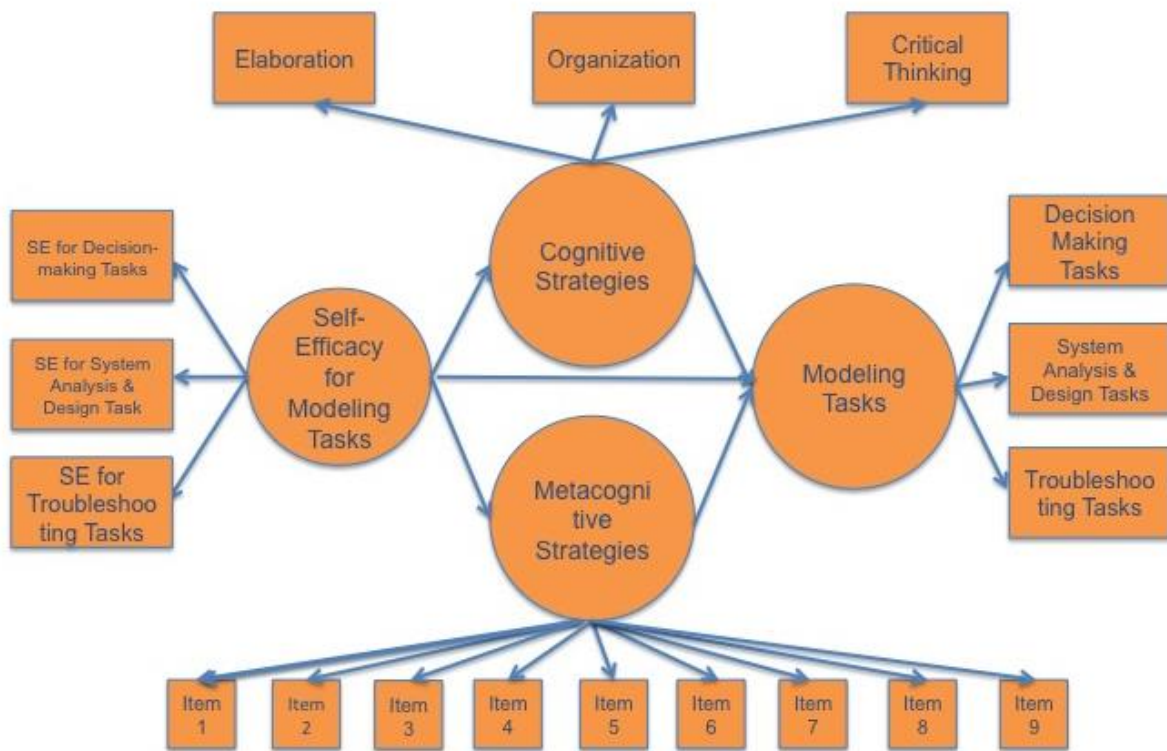


Figure 3-1. The hypothesized model depicting relationships between self-efficacy beliefs, cognitive and metacognitive strategy use, and students' performance on model-eliciting tasks

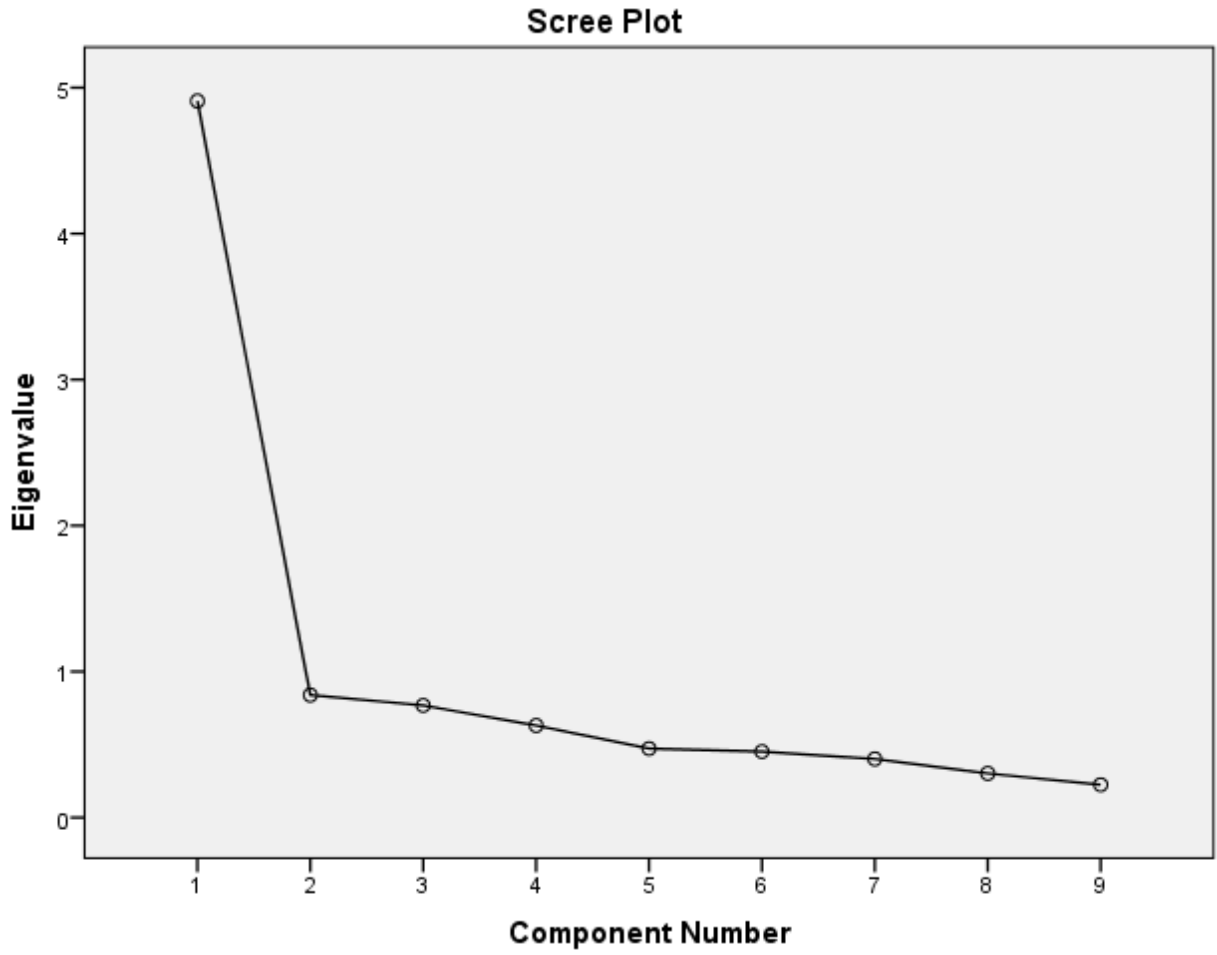


Figure 3-2. The scree plot showing Modeling Self-Efficacy scale as one factor model

	Decision making	System analysis and design	Trouble shooting
Goals	<i>Choosing among alternatives under constraints</i>	<i>Identifying the relationships between parts of a system and/or designing a system to express the relationships between parts</i>	<i>Diagnosing and correcting a faulty or underperforming system or mechanism</i>
Processes involved	<i>Understanding a situation where there are several alternatives and constraints and a specified task</i>	<i>Understanding the information that characterises a given system and the requirements associated with a specified task</i>	<i>Understanding the main features of a system or mechanism and its malfunctioning, and the demands of a specific task</i>
	<i>Identifying relevant constraints</i>	<i>Identifying relevant parts of the system</i>	<i>Identifying causally related variables</i>
	<i>Representing the possible alternatives</i>	<i>Representing the relationships among parts of the system</i>	<i>Representing the functioning of the system</i>
	<i>Making a decision among alternatives</i>	<i>Analysing or designing a system that captures the relationships between parts</i>	<i>Diagnosing the malfunctioning of the system and/or proposing a solution</i>
	<i>Checking and evaluating the decision</i>	<i>Checking and evaluating the analysis or the design of the system</i>	<i>Checking and evaluating the diagnosis/solution</i>
	<i>Communicating or justifying the decision</i>	<i>Communicating the analysis or justifying the proposed design</i>	<i>Communicating or justifying the diagnosis and the solution</i>
Possible sources of complexity	<i>Number of constraints</i>	<i>Number of interrelated variables and nature of relationships</i>	<i>Number of interrelated parts of the system or mechanism and the ways in which these parts interact</i>
	<i>Number and type of representations used (verbal, pictorial, numerical)</i>	<i>Number and type of representations used (verbal, pictorial, numerical)</i>	<i>Number and type of representations used (verbal, pictorial, numerical)</i>

Figure 3-3. Problem-solving (modeling) processes involved in three different types of problem-solving (modeling) tasks (OECD, 2004, p. 29)

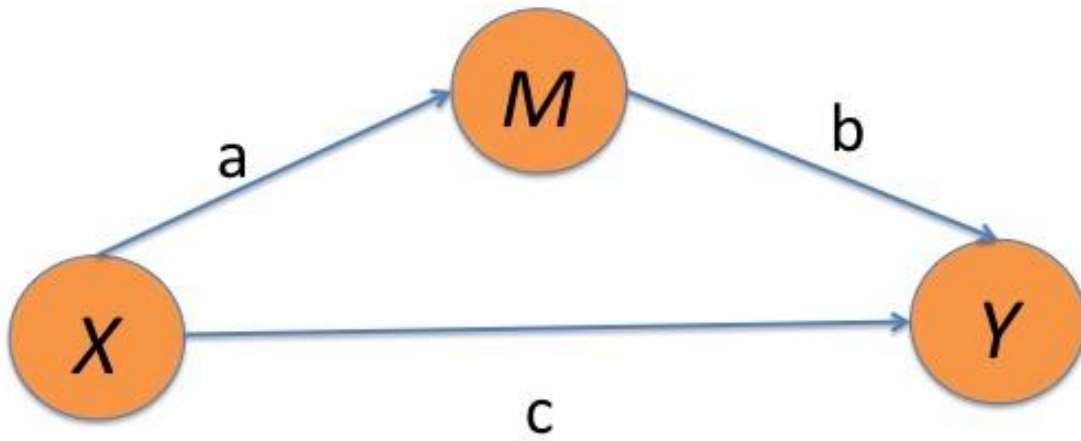


Figure 3-4. A basic mediation model with X as an independent variable, Y as a dependent variable, and M as an intervening variable

CHAPTER 4 RESULTS

This chapter describes results of descriptive analysis including internal consistency of each construct, patterns of missingness, assumptions of structural equation modeling, and Confirmatory Factor Analysis (CFA) of the MSLQ and Modeling Self-Efficacy scales. It also includes results of CFA of the full measurement model and results obtained from testing the structural model.

Descriptive Analysis

Reliability Estimates

Results of the reliability estimate for each scale, provided in Table 4-1, indicated that coefficient alpha ranged from .60 to .89. The reliability estimate of the Modeling Self-Efficacy scale was very high with coefficient alpha equal to .89. As minimum acceptable level of reliability in social sciences varies from .70 to .80, the low reliability estimates of the organization subscale ($\alpha = .61$) and the modeling test ($\alpha = .60$) caused concerns with regard to the results of this study.

Missing Data Analysis

Missing data or observations with missing values were examined by performing missing value analysis. The percentage of missing values for each observed variable was not more than 1% (see Table 4-2) and remained under 3% for each latent construct (see Table 4-3). Since the missingness in each case was under 5%, no missing pattern analysis was conducted. Further, in the present study data were analyzed using the WLSMV estimator, which estimates models by using all the available data except for those cases with missing data on the exogenous observed variables (Muthèn & Muthèn, 2002). As evident from the Table 4-2 there were no missing values for the self-efficacy

variables, which were the exogenous variables in the present study, WLSMV utilized all the available 225 cases without either imputing data or eliminating cases based on the assumption that missingness was completely at random (MCAR).

Descriptive Statistics

Participants' mean scores for each subscale in the MSLQ were calculated by averaging the participants' ratings across all the items on a subscale as recommended in the MSLQ manual (Pintrich et al., 1991). Descriptive analysis of the MSLQ subscales (see Table 4-3) indicated that means of the elaboration ($M = 3.99$, $SD = 1.14$) and organization subscales ($M = 3.92$, $SD = 1.24$) were higher than the critical thinking subscale ($M = 3.62$, $SD = 1.24$). The overall mean score for the metacognitive self-regulation scale was 4.25 ($SD = 1.05$).

Participants' mean self-efficacy scores for each of the six modeling problems were calculated by averaging participants' ratings across all the four self-efficacy questions. For example, the mean self-efficacy score for the Cinema Outing problem was calculated by averaging participants' ratings for understanding the problem, determining a strategy, determining the information, and correctly solving a problem. Table 4-4 shows the descriptive analysis of the Modeling Self-Efficacy scale. Consistent with the pilot study results, eighth- and ninth-grade students reported higher levels of self-confidence in solving the Cinema Outing ($M = 82.02$, $SD = 17.44$) and Children's Camp ($M = 81.00$, $SD = 16.80$) problems than the Energy Needs problem ($M = 76.0$, $SD = 20.34$). Students appeared to be least confident in solving the Course Design ($M = 72.93$, $SD = 21.73$), Irrigation ($M = 71.74$, $SD = 21.61$), and Freezer ($M = 72.16$, $SD = 21.55$) problems.

Students engaged in this study also solved six modeling problems. Some of the problems required a definite solution including yes or no, whereas some problems required students to provide explanations of their solutions. The minimum and maximum scores received by students on each problem vary between 0 and 2. Table 4-5 shows that students earned the highest average score for the Cinema Outing ($M = 0.85$, $SD = 0.62$) and Children's Camp ($M = 0.78$, $SD = 0.72$) problems. These scores were consistent with their high self-efficacy beliefs reported for these tasks. With regard to the Course Design and Freezer problems, there were some inconsistencies between the levels of confidence reported by students and their scores on these problems. Students reported similar levels of confidence for both the problems, but the mean score for the Course Design ($M = 0.77$, $SD = 0.88$) was much higher than the Freezer problem ($M = 0.37$, $SD = 0.49$). The mean for the Energy Needs and Irrigation problems were .74 ($SD = 0.86$) and .43 ($SD = 0.50$), respectively.

Multivariate Normality Assumption

Multivariate normality assumption implies that each individual variable is normally distributed and combinations of such variables are distributed as multivariate normal (Kline, 2005/2011). The departure from normality causes the chi-square test statistic to be larger than expected and standard errors to be smaller than they should be. Although parameter estimates, standard errors, and test statistics in the present study were computed using a robust WLSMV estimator that produces accurate results under both normal and non-normal distributions (Byrne, 2012; Muthèn & Muthèn (2002), it is always a good idea to check the distribution of each variable for univariate normality. The skew and kurtosis values, as presented in Tables 4-3, 4-4 and 4-5, for each variable were within reasonable ranges. Skewness values for each variable were not

greater than 3.0 (e.g., values ranged from -1.632 to 0.530), and kurtosis values stayed much under 10.0 (e.g., values ranged from -1.935 to 3.295). Thus, the assumption of multivariate normality was satisfied.

Confirmatory Factor Analysis of the MSLQ Scale

In an attempt to gather evidence of construct validity for the MSLQ scale, individual parameters, such as factor loadings and factor correlations, were examined through CFA procedures. In general, the values for factor loadings should be moderately high to establish significant relationships between observed indicators and their corresponding latent variables. On the other hand, values for factor correlations should be minimal to discriminate latent variables from one another. The item-level factor analysis of the MSLQ scale provided an acceptable fit to the data in terms of Chi-square, CFI, TLI, and RMSEA fit indices (χ^2 [246 df, N = 225] = 442.55, $p < .001$, CFI = .92, TLI = .91, RMSEA = .06 with 90% CI [.05, .06]). The standardized parameter estimates for the factor loadings, provided in Table 4-6, indicated that all observed indicators had standardized factor loadings on their common factors greater than .30. Further, all indicators (i.e. items on each subscale) in the model had statistically significant standardized factor loadings ($p < .001$) confirming that observed indicators for each construct were correlated.

Construct correlations, presented in Table 4-7, indicated high correlation between latent factors suggesting low discriminant validity between them. Specifically, statistically significant correlations were found between metacognitive self-regulation scale and indicators of the cognitive strategies such as elaboration ($r = .876$, $p < .001$), critical thinking ($r = .730$, $p < .001$), and organization ($r = .716$, $p < .001$) subscales.

Such high correlations were also found in Kaya (2007) study that used the same version of the MSLQ. These correlations were expected because one of the important aspects of metacognitive strategies is to enable learners to control, monitor, and regulate their cognitive processes, which involve the use of elaboration, organization, and critical thinking strategies (Pintrich, 2002; Pintrich et al., 1993). The high correlations between metacognitive self-regulation and elaboration, organization, and critical thinking subscales suggested potential multicollinearity problems between metacognitive self-regulation and cognitive strategies scale.

Confirmatory Factor Analysis of the Modeling Self-Efficacy Scale

Before model testing, CFA of the Modeling Self-Efficacy scale was conducted to investigate whether the factor-loading pattern established during the pilot study fits the data from a new sample. The CFA for the Modeling Self-Efficacy scale was conducted by loading participants' mean ratings for the six modeling problems, calculated across four self-efficacy questions, on the overall modeling self-efficacy latent variable. For example, "sedm1" represents participants' mean rating for the Cinema Outing problem calculated over four self-efficacy items including understanding the problem, determining a strategy, determining information, and solving the problem. The goodness of fit indices such as chi-square, RMSEA, CFI, and TLI indicated that the model fits the data well (χ^2 [9 df, N = 225] = 13.48, $p = .14$, CFI = .99, TLI = .99, RMSEA = .05 (with 90% CI lower bound = .00 and upper bound = .10)). Parameter estimates shown in Table 4-8 indicated that each observed variable had statistically significant ($p < .001$) standardized factor loading on the overall Modeling Self-Efficacy scale.

Overview of Model Testing

Model testing in the current study was performed by using the two-step modeling approach including verifying the measurement model and testing the full Structural Equation Model (Kline, 2005/2011). During the first step, confirmatory factor analysis of the measurement model is performed to determine relationships between the observed indicators and the continuous latent variables. On obtaining an acceptable measurement model, the second part of the two-step modeling procedure is performed to test relationships among latent variables. As such, under the full SEM model both the measurement and structural models are tested.

Results of a confirmatory factor analysis indicated an acceptable fit of the data with the hypothesized measurement model. The goodness-of-fit test results were χ^2 [129 df, N = 225] = 250.60, $p < .001$, CFI = .92, TLI = .90, and RMSEA = .06 with 90% CI [.05, .07]. Further, all observed indicators in the model had statistically significant ($p < .001$) standardized factor loadings on their corresponding latent factors. As expected, a large correlation ($r = .96$, $p < .001$) was found between cognitive and metacognitive factors indicating multicollinearity problems. In order to improve the model-fit and to reduce correlations between the cognitive and metacognitive factors, modification indices for the measurement model were reviewed to check for adding cross-loadings between metacognitive factor indicators (e.g., nine metacognitive items) and cognitive factor indicators (e.g., elaboration, organization, and critical thinking). However, no cross-loadings were found between these two highly correlated factors. In such cases, Grewal, Corte, and Baumgartner (2004) suggest re-specifying the statistical model.

Accordingly, the latent cognitive factor in the original model was replaced by three latent factors including elaboration, organization, and critical thinking.

The modified model (see Figure 4-1) provided a much better fit to the data with regard to CFI (.94), TLI (.94), and RMSEA (.05 with 90% CI lower bound = .04 and upper bound = .06) fit indices. However, Chi-square statistics (χ^2 [390 df, N = 225] = 595.97, $p < .001$) suggested a large discrepancy between the sample covariance matrix and the restricted population covariance matrix. As depicted in Figure 4-2, the model consisted of six correlated latent factors including self-efficacy for modeling tasks, metacognitive, critical thinking, organization, elaboration strategies, and modeling tasks.

Standardized factor loadings, factor correlations, and R^2 estimates are presented in Table 4-9, 4-10, and 4-11. The evaluation of the factor loadings in Table 4-9 indicated that all the observed indicators had standardized factor loadings greater than .30 on their common factors, which suggested that they adequately represent their underlying latent variables. The ratio of each parameter estimate to its corresponding standard error was greater than 1.96, indicating that all the estimates were statistically significant. All the standard errors were in good order since they were neither very large nor too small. Excessively large standard errors make the test statistic for the related parameters difficult to compute and standard errors approaching zero result in undefined test statistic (Bentler as cited in Byrne, 2012).

On reviewing factor correlations presented in Table 4-10, it was found that some of the bivariate correlations among latent factors were in the expected directions while others were troublesome. Students' self-efficacy beliefs for modeling tasks were found to correlate positively with students' reported use of cognitive strategies such as critical

thinking ($r = .383, p < .001$) and elaboration ($r = .320, p < .001$) as well as metacognitive strategies ($r = .330, p < .001$). Also, self-efficacy beliefs had a significant moderate correlation with students' success rate on modeling tasks ($r = .542, p < .001$). However, correlations between modeling self-efficacy beliefs and organization strategies were not significant at the .05 level ($r = .009, p = .910$). Similar inappropriate relationships were observed among other variables as well. Specifically, insignificant correlations were found between students' reported use of metacognitive strategies ($r = .095, p = .288$) and their success rate in the area of mathematical modeling. Critical thinking strategies ($r = .029, p = .769$) and elaboration strategies ($r = .058, p = .517$) also did not correlate significantly with students' performance on the modeling test. Further, a significant negative correlation was found between organization strategies and modeling task success ($r = -.277, p = .005$).

As found in the CFA for the MSLQ, high correlations existed between metacognitive strategies and critical thinking ($r = .731, p < .001$), organization ($r = .714, p < .001$), and elaboration ($r = .876, p < .001$) strategies. Kline (2005) specified that correlations higher than .85 lead to multicollinearity problems. Thus, high correlations between elaboration and metacognitive self-regulation factors caused concerns for multicollinearity. Therefore, Modification Index (MI) values, as presented in Table 4-12, were reviewed to identify whether observed indicators of elaboration, critical thinking, and metacognitive factors were cross-loading on more than one factor. For the purposes of this study, parameters having MI values greater than or equal to 10.00 were reported. On inspecting these parameters, it was found that most of the MI values were very small and not worthy of inclusion in a subsequent model. For example, a MI

value of 11.39 suggested that if ORG, which was designed to measure organization strategies, were to load additionally onto metacognitive factor, the overall model Chi-square value would decrease by 11.39. Moreover, such modifications (e.g., combining organization and metacognitive subscales) did not make sense theoretically because organization, elaboration, critical thinking, and metacognitive self-regulations are distinct constructs (Pintrich et al., 1991). As such, no further actions were taken.

R^2 estimates reported in Table 4-11 represent the proportion of variance in each observed variable that can be explained by the latent construct to which it is linked. All R^2 estimates were found to be reasonable as well as statistically significant except two weak indicators, ELAB1, measuring students' reported use of elaboration strategies, and TS, measuring students' success rate on troubleshooting tasks, that had R^2 values equal to .18 and .18, respectively.

Research Hypotheses Testing

The full structural model was estimated by specifying all the structural regression paths including effects of self-efficacy beliefs on students' self-reported use of elaboration, organization, critical thinking, and metacognitive strategies; effects of self-efficacy beliefs and use of elaboration, organization, critical thinking, and metacognitive strategies on students' performance on modeling tasks; indirect effects of self-efficacy beliefs on modeling tasks success via use of elaboration, organization, critical thinking, and metacognitive strategies. Unfortunately, estimation of the full structural model did not converge when the default starting values supplied by Mplus were used. As a result, the measurement model was estimated again with 'SVALUES' option that asks Mplus to produce a model statement, which includes final estimates as the starting values (Muthèn & Muthèn, 1998-2012). On using these starting values, the model estimation

terminated normally. The full structural model fit adequately to the given data with regard to CFI, TLI, and RMSEA fit indices (χ^2 [390 df, N = 225] = 595.97, $p < .001$, CFI = .95, TLI = .94, RMSEA = .05 (with 90% CI lower bound = .04 and upper bound = .06)).

As presented in Figure 4-2 and Table 4-13, eighth- and ninth-grade self-efficacy beliefs for modeling tasks showed significant positive direct effects on critical thinking ($\beta = .38$, $p < .001$), elaboration ($\beta = .32$, $p < .001$), and metacognitive strategies ($\beta = .33$, $p < .001$). This implies that students' who perceived themselves capable of solving and understanding mathematical modeling tasks also reported the use of these strategies. Surprisingly, results indicated that perceived modeling self-efficacy ($\beta = .009$, $p = .910$) did not correlate significantly with participants' organization strategy use. Therefore, no credible evidence was found to support an association between modeling self-efficacy and organization strategy use.

Perceived modeling self-efficacy ($\beta = .50$, $p < .001$) directly positively predicted students' performance in solving modeling problems correctly. In other words, students who reported greater self-efficacy for solving modeling tasks were more likely to correctly solve the modeling problems. Contrary to the hypothesized relationship, organization strategy use ($\beta = -.62$, $p = .004$) had a significant negative direct effect on students' performance on the modeling test. This means that students who reported using more organization strategies tended to get lower scores on the modeling test. Further, direct effects of students' use of critical thinking ($\beta = -.59$, $p = .08$), elaboration ($\beta = .40$, $p = .41$), and metacognitive strategies ($\beta = .46$, $p = .16$) on their performance in solving modeling tasks were non-significant. Therefore, the data did not provide any

evidence of the direct effects of critical thinking, elaboration, and metacognitive strategies on their performance in modeling-ability test.

As reported earlier, students' perceived self-efficacy for modeling tasks directly predicted their reported use of critical thinking, elaboration, and metacognitive strategies but the direct effects of cognitive and metacognitive strategies on modeling task success were non-significant. As expected, the indirect effects of students' self-efficacy for modeling on their performance in solving modeling tasks through its effect on their use of critical thinking ($\beta = -.225, p = .10$), organization ($\beta = -.006, p = .91$), elaboration ($\beta = .128, p = .41$), and metacognition strategies ($\beta = .15, p = .18$) were non-significant.

Table 4-1. Summary of reliability estimates of each scale

Scales	Cronbach's alpha	Number of Items
Self-efficacy	.89	6
Elaboration	.73	6
Organization	.61	4
Critical thinking	.76	5
Metacognitive self-regulation	.78	9
Modeling test	.60	6

Note. $N = 225$

Table 4-2. Missing data analysis for the observed indicators of the full model

	N	M	S.D.	Missing Count	Percent
MSLQ					
elab1	225	4.73	1.77	0	0.0
elab2	225	3.79	1.83	0	0.0
elab3	225	5.03	1.71	0	0.0
elab4	225	2.13	1.56	0	0.0
elab5	225	4.38	1.76	0	0.0
elab6	224	3.90	1.87	1	0.4
org1	225	2.96	1.61	0	0.0
org2	225	5.05	1.80	0	0.0
org3	225	3.10	1.88	0	0.0
org4	225	4.59	1.99	0	0.0
ct1	225	3.89	1.72	0	0.0
ct2	225	5.05	1.80	0	0.0
ct3	225	3.52	1.65	0	0.0
ct4	225	3.82	1.84	0	0.0
ct5	225	3.38	1.77	0	0.0
mcsr1	224	5.29	1.50	1	0.4
mcsr2	224	3.17	1.65	1	0.4
mcsr3	225	3.61	2.03	0	0.0
mcsr4	225	4.27	1.84	0	0.0
mcsr5	225	3.64	1.64	0	0.0
mcsr6	225	4.14	1.60	0	0.0
mcsr7	225	5.45	1.58	0	0.0
mcsr8	225	4.13	1.94	0	0.0
mcsr9	224	3.90	1.87	1	0.4
Self-Efficacy Scale					
q1se1	225	83.78	18.52	0	0.0
q1se2	225	79.47	20.17	0	0.0
q1se3	225	83.64	18.15	0	0.0
q1se4	225	81.20	19.84	0	0.0
q2se1	225	77.78	21.05	0	0.0
q2se2	225	74.84	21.15	0	0.0
q2se3	225	77.07	21.98	0	0.0
q2se4	225	74.58	22.73	0	0.0
q3se1	225	82.58	17.56	0	0.0
q3se2	225	79.51	18.40	0	0.0
q3se3	225	82.62	17.02	0	0.0
q3se4	225	79.29	19.19	0	0.0
q4se1	225	75.24	21.85	0	0.0
q4se2	225	71.47	22.36	0	0.0
q4se3	225	74.53	22.51	0	0.0
q4se4	225	70.49	24.26	0	0.0
q5se1	225	72.62	22.61	0	0.0
q5se2	225	71.07	21.62	0	0.0
q5se3	225	72.89	22.56	0	0.0

Table 4-2. Continued

	N	M	S.D.	Missing	
				Count	Percent
Self-Efficacy Scale					
q5se4	225	70.40	24.13	0	0.0
q6se1	225	73.33	20.98	0	0.0
q6se2	225	71.07	22.09	0	0.0
q6se3	225	73.91	22.37	0	0.0
q6se4	225	70.36	24.30	0	0.0
Modeling Tasks					
mod1	219	0.85	0.62	6	2.7
mod2	219	0.74	0.86	6	2.7
mod3	219	0.78	0.72	6	2.7
mod4	219	0.77	0.87	6	2.7
mod5	219	0.43	0.49	6	2.7
mod6	219	0.37	0.48	6	2.7

Note. MCSR = Metacognitive Self-Regulation, ELAB = Elaboration, ORG = Organization, CT = Critical Thinking, mod1 = Cinema Outing, mod2 = Energy Needs, mod3 = Children's Camp, mod4= Course Design, mod5 = Irrigation, mod6 = Freezer problems

Table 4-3. Missing Value Analysis for each construct

	N	M	S.D.	Missing		Skewness	Kurtosis
				Count	Percent		
Elaboration	225	3.99	1.14	0	0.0	-0.102	-0.303
Organization	225	3.92	1.24	0	0.0	-0.139	-0.341
Critical Thinking	225	3.62	1.24	0	0.0	0.297	-0.269
MCSR	225	4.25	1.05	0	0.0	-0.385	-0.100
Self-Efficacy	225	75.98	18.24	0	0.0	-0.884	0.721
Modeling Tasks	219	3.93	2.41	6	2.7	0.229	-0.954

Note. MCSR = Metacognitive Self-Regulation

Table 4-4. Descriptive statistics for the Modeling Self-Efficacy scale

	N	M	S.D.	Skewness	Kurtosis
SE1	225	82.02	17.44	-1.632	3.295
SE2	225	76.06	20.34	-1.012	0.609
SE3	225	81.00	16.80	-1.214	1.627
SE4	225	72.93	21.73	-0.898	0.284
SE5	225	71.74	21.61	-0.672	-0.354
SE6	225	72.16	21.55	-0.882	0.382

Note. SE1 = Self-efficacy for Cinema Outing, SE2 = Self-efficacy for Energy Needs, SE3 = Self-efficacy for Children's Camp, SE4 = Self-efficacy for Course Design, SE5 = Self-efficacy for Irrigation, SE6 = Self-efficacy for Freezer problems

Table 4-5. Descriptive statistics for the modeling test

Problems	N	Min	Max	M	S.D.	Skewness	Kurtosis
Cinema	219	0.00	2.00	0.85	0.621	0.111	-0.474
Outing							
Energy	219	0.00	2.00	0.74	0.862	0.530	-1.452
Needs							
Children's	219	0.00	2.00	0.78	0.723	0.367	-1.025
Camp							
Course	219	0.00	2.00	0.77	0.876	0.473	-1.535
Design							
Irrigation	219	0.00	1.00	0.43	0.496	0.288	-1.935
Freezer	219	0.00	1.00	0.37	0.485	0.522	-1.743

Note. N = 225 (Six students did not complete the modeling test)

Table 4-6. Confirmatory Factor Analysis of MSLQ subscales with WLSMV parameter estimate

Parameter	Standardized Factor Loading	Standard Error	Est./S.E.	Two-tailed p-value
MCSR1	.56	.05	11.55	.000
MCSR2	.54	.05	11.15	.000
MCSR3	.53	.05	10.46	.000
MCSR4	.67	.04	15.67	.000
MCSR5	.51	.05	9.53	.000
MCSR6	.62	.05	13.12	.000
MCSR7	.52	.06	9.50	.000
MCSR8	.55	.05	11.17	.000
MCSR9	.48	.06	8.73	.000
CT1	.47	.06	7.58	.000
CT2	.71	.04	18.40	.000
CT3	.69	.04	17.95	.000
CT4	.59	.05	11.98	.000
CT5	.76	.04	19.19	.000
ORG1	.63	.06	10.94	.000
ORG2	.50	.06	8.58	.000
ORG3	.49	.07	7.19	.000
ORG4	.69	.06	12.18	.000
ELAB1	.44	.05	8.19	.000
ELAB2	.62	.04	14.03	.000
ELAB3	.61	.04	14.11	.000
ELAB4	.56	.06	10.14	.000
ELAB5	.67	.04	17.49	.000
ELAB6	.70	.04	20.26	.000

Note. MCSR = Metacognitive Self-Regulation, ELAB = Elaboration, ORG = Organization, CT = Critical Thinking

Table 4-7. Estimated correlation matrix for the latent variables

	MCSR	Critical Thinking	Organization	Elaboration
MCSR	1.000			
Critical Thinking	.730	1.000		
Organization	.716	.402	1.000	
Elaboration	.876	.862	.632	1.000

Key: $p < .05$, MCSR = Metacognitive Self-Regulation

Table 4-8. Confirmatory Factor Analysis of Modeling Self-Efficacy scale with WLSMV estimator

Parameter	Standardized Factor Loading	Standard Error	Est./S.E.	Two-tailed p-value
SE1	.72	.04	19.47	.000
SE2	.82	.03	30.58	.000
SE3	.75	.03	21.98	.000
SE4	.75	.03	22.54	.000
SE5	.77	.03	24.18	.000
SE6	.79	.03	26.48	.000

Note. SE1 = Self-efficacy for Cinema Outing, SE2 = Self-efficacy for Energy Needs, SE3 = Self-efficacy for Children's Camp, SE4 = Self-efficacy for Course Design, SE5 = Self-efficacy for Irrigation, SE6 = Self-efficacy for Freezer problems

Table 4-9. Confirmatory Factor Analysis for the full measurement model

Parameter	Standardized Factor Loading	Standard Error	Est./S.E.	Two-Tailed P-value
Modeling Self-Efficacy				
SE-DM	.89	.02	45.18	.000
SE-SAD	.85	.02	38.55	.000
SE-T	.84	.02	39.98	.000
MSLQ Subscales				
MCSR1	.57	.05	11.88	.000
MCSR2	.53	.05	10.88	.000
MCSR3	.52	.05	9.85	.000
MCSR4	.68	.04	15.58	.000
MCSR5	.49	.05	9.19	.000
MCSR6	.62	.05	13.02	.000
MCSR7	.53	.05	9.79	.000
MCSR8	.55	.05	10.76	.000
MCSR9	.49	.05	8.97	.000
CT1	.45	.06	7.30	.000
CT2	.71	.04	18.27	.000
CT3	.69	.04	18.01	.000
CT4	.61	.05	12.29	.000
CT5	.77	.04	19.68	.000
ORG1	.63	.06	11.18	.000
ORG2	.50	.06	8.55	.000
ORG3	.49	.07	7.30	.000
ORG4	.67	.06	12.44	.000
ELAB1	.43	.05	7.96	.000
ELAB2	.62	.04	14.05	.000
ELAB3	.62	.04	14.06	.000
ELAB4	.55	.05	9.74	.000
ELAB5	.68	.03	18.00	.000
ELAB6	.70	.03	19.66	.000
Modeling Tasks				
Decision-making tasks	.56	.07	7.59	.000
System analysis tasks	.70	.08	8.56	.000
Troubleshooting tasks	.42	.08	4.96	.000

Note. SE-DM = Self-Efficacy for Decision-making tasks, SE-SAD = Self-Efficacy for System Analysis and Design tasks, and SE-T = Self-Efficacy for Troubleshooting tasks. MCSR = Metacognitive Self-Regulation, ELAB = Elaboration, ORG = Organization, CT = Critical Thinking

Table 4-10. Correlations among latent variables

Parameter		Standardized Correlations	Standard Error	Est./S.E.	Two-Tailed P-value
MCSR	SE	.33	.07	4.82	.000
CT	SE	.38	.07	5.85	.000
CT	MCSR	.73	.04	18.14	.000
ORG	SE	.01	.08	0.11	.910
ORG	MCSR	.71	.05	14.39	.000
ORG	CT	.40	.07	5.74	.000
ELAB	SE	.32	.07	4.60	.000
ELAB	MCSR	.87	.03	29.01	.000
ELAB	CT	.86	.04	24.21	.000
ELAB	ORG	.63	.06	10.34	.000
Modeling Tasks	SE	.54	.08	7.17	.000
Modeling Tasks	MCSR	.10	.09	1.06	.288
Modeling Tasks	CT	.03	.10	0.29	.769
Modeling Tasks	ORG	-.28	.10	-2.82	.005
Modeling Tasks	ELAB	.06	.09	0.65	.517

Note. MCSR = Metacognitive Self-Regulation, ELAB = Elaboration, ORG = Organization, CT = Critical Thinking, SE = Self-Efficacy

Table 4-11. R² estimates for each observed and latent dependent variable in the model

Observed Variable	Estimate	Standard Error	Est./S.E.	Two-Tailed P-value
Self-Efficacy (decision-making)	.79	.03	22.59	.000
Self-Efficacy (system analysis)	.73	.04	19.28	.000
Self-Efficacy (troubleshooting)	.71	.04	19.99	.000
MCSR1	.33	.06	5.94	.000
MCSR2	.28	.05	5.44	.000
MCSR3	.27	.05	4.93	.000
MCSR4	.46	.06	7.79	.000
MCSR5	.24	.05	4.60	.000
MCSR6	.39	.06	6.51	.000
MCSR7	.28	.06	4.90	.000
MCSR8	.30	.05	5.38	.000
MCSR9	.24	.05	4.48	.000
CT1	.21	.06	3.65	.000
CT2	.50	.06	9.13	.000
CT3	.48	.05	9.00	.000
CT4	.37	.06	6.15	.000
CT5	.59	.06	9.84	.000
ORG1	.40	.07	5.59	.000
ORG2	.25	.06	4.28	.000
ORG3	.24	.07	3.65	.000
ORG4	.45	.07	6.22	.000
ELAB1	.18	.05	3.98	.000
ELAB2	.39	.06	7.03	.000
ELAB3	.38	.05	7.03	.000
ELAB4	.30	.06	4.87	.000
ELAB5	.46	.05	8.99	.000
ELAB6	.49	.05	9.83	.000
Decision-making tasks	.31	.08	3.80	.000
System-analysis tasks	.50	.12	4.28	.000
Troubleshooting tasks	.18	.07	2.48	.013

Note. MCSR = Metacognitive Self-Regulation, ELAB = Elaboration, ORG = Organization, CT = Critical Thinking

Table 4-12. Model Modification Indices

Parameters		M.I.	E.P.C.
CT	BY ELAB1	12.09	-1.36
ORG	BY MCSR1	11.39	-0.56
ORG	BY ELAB1	21.43	0.63
ORG	BY ELAB2	16.66	-0.60
ORG	BY ELAB4	17.34	0.63

Note. MCSR = Metacognitive Self-Regulation, ELAB = Elaboration, ORG = Organization, CT = Critical Thinking, M.I. = Modification Index, E.P.C. = Expected Parameter Change

Table 4-13. Standardized estimates of the path coefficients in the full structural equation model

Parameter	Standardized Estimate	Standard Error	Est./S.E.	Two-Tailed p-value
Self-Efficacy ON Critical Thinking	.38	.07	5.42	.000
Self-Efficacy ON Organization	.01	.08	0.11	.910
Self-Efficacy ON Elaboration	.32	.07	4.60	.000
Self-Efficacy ON Metacognitive	.33	.07	4.82	.000
Critical Thinking ON Modeling tasks	-.59	.35	-1.70	.088
Organization ON Modeling Tasks	-.62	.21	-2.90	.004
Elaboration ON Modeling Tasks	.40	.49	0.81	.417
Metacognitive ON Modeling Tasks	.46	.33	1.40	.161
Self-Efficacy ON Modeling tasks	.50	.10	4.78	.000

Note. Statistically significant paths are in boldface.

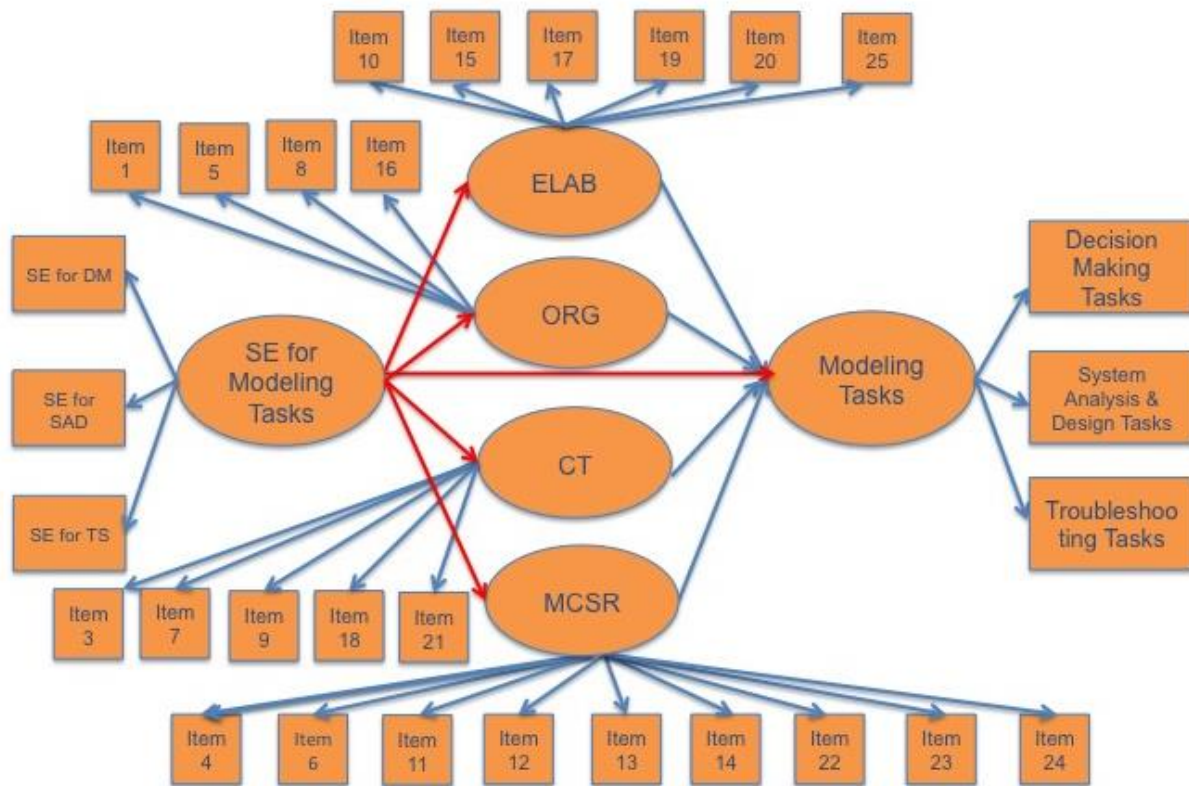


Figure 4-1. The modified measurement model depicting relationships between modeling self-efficacy beliefs, use of elaboration, organization, critical thinking, metacognitive strategies, and modeling task success.

Note. SE for DM = Self-Efficacy for Decision-making tasks, SE for SAD = Self-Efficacy for System Analysis Design tasks, SE for TS = Self-Efficacy for Troubleshooting tasks, MCSR = Metacognitive Self-Regulation, ELAB = Elaboration, ORG = Organization, CT = Critical Thinking

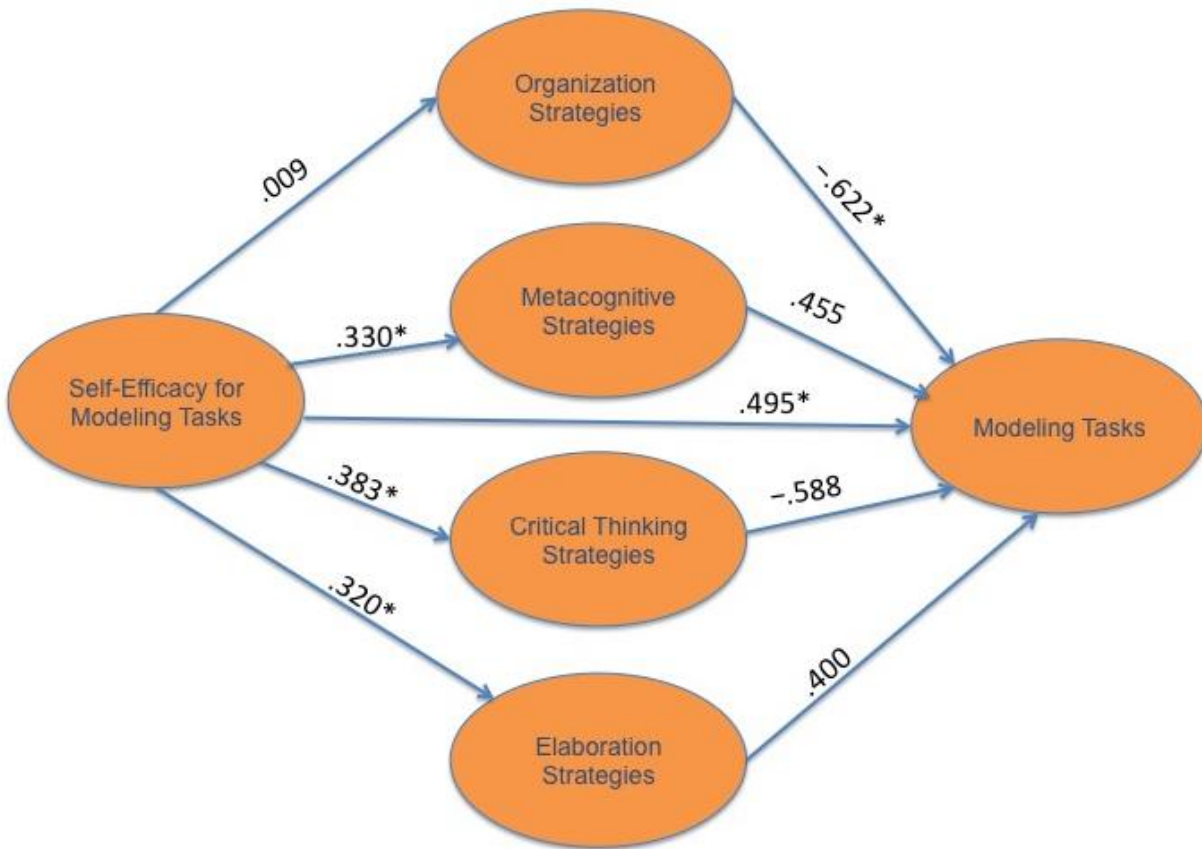


Figure 4-2. Standardized path coefficients in the full structural model.

Note. * $p < .05$

CHAPTER 5 DISCUSSION

Summary of the Findings

The primary purpose of this study was to examine associations between self-efficacy beliefs, self-regulated learning behaviors, and students' modeling outcomes. Towards this end, three research hypotheses were tested. First, students' self-efficacy beliefs for the modeling tasks were hypothesized to have a positive direct influence on their ability to correctly solve problems on the modeling test. Second, students' self-reported use of cognitive and metacognitive strategies was hypothesized to directly influence their performance on the modeling test. Third, students' self-efficacy beliefs for modeling tasks were hypothesized to have a positive indirect influence on their performance on the modeling test through the positive effect on their use of cognitive and metacognitive strategies. This investigation was guided by prior research indicating students' beliefs about their competence (e.g., Pajares & Miller, 1994; Pajares & Kranzler, 1995; Nicolidau & Philippou, 2004) as well as their self-reported use of cognitive and metacognitive strategies (e.g., Pape & Wang, 2003; Pintrich & DeGroot, 1990; Zimmerman & Martinez-Pons, 1986, 1988, 1990) significantly influence students' problem-solving and mathematics achievement.

The present study, however, is different from these studies in a few respects. First, the present study examined the influence of self-efficacy beliefs and SRL strategy use on students' success in solving complex real-world problems (i.e., modeling tasks). Second, research studies such as Bouffard-Bouchard et al. (1991), Mousoulides and Philippou (2005), Pintrich and DeGroot (1990), and Kaya (2007) studied the impact of SRL strategy use by indicating elaboration, critical thinking, and organization strategies

as observed indicators for the cognitive strategy latent variable. Owing to high multicollinearity found between cognitive and metacognitive strategy scales, the present study used items on the MSLQ to define elaboration, critical thinking, and organization latent variables in the modified measurement model rather than including them as observed indicators for defining the cognitive latent variable.

There is strong evidence that students' beliefs about their competence are related to as well as predictive of their problem-solving achievement (Chen, 2003; Greene et al., 2004; Nicolidou & Philippou, 2004; Pajares & Graham, 1999; Pajares & Kranzler, 1995; Pajares & Miller, 1994; Pajares & Valiante, 2001; Pintrich & DeGroot, 1990). Consistent with the problem-solving literature, the findings of the present study indicated that self-efficacy beliefs are associated with students' success in modeling tasks. That is, students who reported higher levels of confidence for understanding modeling tasks were more successful in solving these tasks. Further, research has shown that students who believe in their competence are more likely to employ sophisticated cognitive and metacognitive strategies to understand and solve academic or problem-solving tasks (Bouffard-Bouchard et al., 1991; Greene et al., 2004; Pintrich & DeGroot, 1990; Zimmerman & Bandura, 1984; Zimmerman & Martinez-Pons, 1990). Similarly, the findings of the present investigation indicated that self-efficacy beliefs were significantly associated with students' self-reported use of cognitive and metacognitive strategies. Specifically, students who perceived themselves capable of understanding and solving modeling tasks also tended to report using elaboration, critical thinking, and metacognitive strategies as they engage in mathematical activities.

The present study, however, did not find significant association between self-efficacy beliefs and students' self-reported use of organization strategies.

Further, significant associations have been identified in the literature between SRL strategy use and student problem-solving performance (Pape & Wang, 2003; Pintrich & DeGroot, 1990; Zimmerman & Martinez-Pons, 1986, 1988, 1990). These studies have established that students who are successful in solving problem-solving tasks tend to report using more sophisticated learning strategies. These results were not confirmed in the present study because no significant associations were found between students' reported use of elaboration, critical thinking, and metacognitive strategies and their success on the modeling tasks. The use of organization strategies, however, was negatively associated with students' performance on the modeling test. That is, students who reported higher use of organization strategies received lower scores on the modeling test. This result was also found in previous studies (e.g., Mousoulides & Philippou, 2005; Kaya, 2007) although they examined the direct effect of cognitive strategy use on students' mathematics achievement. The negative association between the self-reported use of organization strategies and students' performance on the modeling tasks might have occurred because of the low reliability estimate ($\alpha = .61$) of the organization scale indicating that items on the scale might not be consistently measuring the required construct.

With regard to the third objective of this study, the findings of the present study contradict earlier assertions made by Bouffard-Bouchard et al. (1991), Heidari et al. (2012), Pintrich and DeGroot (1990), and Zimmerman and Bandura (1994). Specifically, the findings did not provide evidence for the indirect effects of self-efficacy

beliefs on students' success in solving modeling problems through its influence on elaboration, organization, critical thinking, and metacognitive strategy use. These results were expected because no significant associations were found between the mediating variables (i.e., elaboration, organization, critical thinking, and metacognitive strategies) and the dependent variable (i.e., the modeling task success) (Zhao, Lynch, & Chen, 2009).

Further, the current study attempted to provide a valid and reliable instrument to measure students' confidence in solving modeling tasks. The reliability of the Modeling Self-Efficacy scale evaluated during the pilot and main studies indicated that the items consistently measured students' self-efficacy beliefs for understanding and solving modeling tasks ($\alpha = .89$). The construct validity of the scale established using confirmatory factor analysis revealed that the items had significantly high factor loadings, ranging from .72 to .82, on the overall modeling self-efficacy latent variable. These findings suggest that the Modeling Self-Efficacy scale is a dependable instrument that can be used in future studies to measure students' perceived confidence for solving modeling tasks.

Reasons for Inconsistent Results and Recommendations for Future Research

In this section, possible reasons for finding results inconsistent with the past literature will be explored and based on that recommendations for future research projects will be offered. One of the possible explanations would be that the MSLQ instrument might not be appropriate for measuring students' use of cognitive and metacognitive strategies in relation to real-world problem solving. The MSLQ is a retrospective measure requiring students to self-report their use of SRL strategies

based on recollections of past experiences (Zimmerman, 2008). Further, self-reports such as the MSLQ provide information about students' global self-regulatory behaviors (Cleary as cited in National Research Council, 2011). Cleary stated that self-reports "capture the characteristics of self-regulated learning but they do so in a decontextualized manner" (National Research Council, 2011, p. 88). He indicated two potential problems of using self-reports to measure students' SRL behaviors. First, there are validity issues involved in using self-report questionnaires that do not measure context-specific SRL behaviors. There is evidence that students' frequency of self-reporting SRL behaviors varies across tasks as well as subject areas (Zimmerman & Martinez-Pons, 1986, 1988, 1990). Second, self-reports are often incongruent with the strategies actually employed by students in doing specific academic tasks (Winnie & Jamieson-Noel, 2002). This mismatch between the strategies reported and actually used again indicates that students use different learning strategies for different tasks.

In contrast to using self-report measures, future research studies should consider using event measures such as observing students' behaviors when they are actually involved in solving modeling tasks, personal diaries in which students record their thoughts and problem-solving strategies toward solving modeling problems, and think-aloud interviews to measure students' use of SRL strategies before, during and after engaging in modeling tasks (Cleary as cited in National Research Council, 2011; Zimmerman, 2008). Although these measures are very time consuming, they provide a more reliable estimate of students' SRL behaviors. Another suggestion would be modifying items on the MSLQ scale to more closely align with the strategies used by students when engaged in modeling activities. For example, one of the elaboration

items used in this study was: When I study for this class, I pull together information from different sources such as lectures, readings, and discussions we have in class. A revised elaboration item more applicable within the modeling context might be: I solve math problems in everyday life by applying math learned in school (e.g., through lectures, readings, math text book and discussions). An organization item used in this study was: When I study the readings (your mathematics textbook) for this course, I outline the material to help me organize my thoughts. This item could be revised as: When I read math problems that are not immediately resolvable, I outline the material to help me organize my thoughts.

Second, it is likely that the eighth- and ninth-grade students who participated in this study might not have enough experience solving real-world PISA problems. The low reliability estimate ($\alpha = .60$) of the modeling test further indicates that the test was not consistently measuring the desired construct (i.e., students' modeling skills) although it is well documented in the mathematical modeling literature that PISA problems are valid to test students' modeling capabilities (Blum, 2011; Mousoulides, 2007; Mousoulides, Christou, & Sriraman, 2008). Perhaps, pilot testing PISA problems for item difficulty and item discrimination might have resulted in developing a modeling test that more reliably measures students' individual differences in solving modeling tasks.

Third, students' responses on the modeling test were scored in accordance with the rubric used by PISA 2003 problem-solving assessment (see Appendix E). This rubric was selected because it was assumed appropriate to score students' responses with the same scoring system from where these problems were obtained. However, the PISA scoring guide might be conservative because it didn't give students partial credit

for correctly solving many of the sub-questions or performing many of the mathematical steps. As such, it resulted in restricting the variance of scores. For example, the Cinema Outing problem required students to answer all six multiple-choice questions correctly in order to receive full credit (i.e., 2 points). Students did not earn partial credit even if they answered four out of six multiple-choice questions correctly. Similarly, in the Irrigation and Freezer problems students received full credit for answering all three multiple-choice questions correctly. They did not earn partial points for correctly answering one or two of the required three sub-questions. This narrow scoring rubric restricted the range of scores and may not be appropriate for grading students' responses on the modeling test. Perhaps a more robust and comprehensive rubric that provides students partial credit for correctly answering even sub-questions would have been more suitable. Thus, future investigation might include developing a more comprehensive scoring rubric for the modeling test.

Contributions to the Field

The primary objective of this study was to examine relationships between self-efficacy beliefs for solving complex modeling tasks, self-reported use of cognitive and metacognitive strategies, and the direct and indirect effects of these variables on students' success in solving real-world modeling tasks. The present study contributed to research in mathematics education in several ways. A significant contribution of this study to the mathematics education literature was the creation of a statistical model connecting self-efficacy beliefs and SRL strategy use with students' modeling outcomes. This model responded to a need in mathematical modeling research by investigating factors that might influence students' success in solving modeling tasks. The fit indices for the measurement model suggested an adequate fit for the data and

structural model indicated positive association between self-efficacy beliefs and students' modeling task success. Further, considering self-efficacy beliefs have never been studied in relation to students' understanding of real-world modeling problems, the significant relationship established between these constructs contributes significantly to both academic self-efficacy and mathematical modeling literature.

Another significant contribution of this study is the development of a reliable and valid scale measuring students' self-efficacy beliefs for correctly solving real-world modeling tasks. In the field of educational psychology, self-efficacy beliefs have been found to strongly influence individuals' motivation, persistence, effort expended, achievement, and self-regulation (Schunk & Mullen, 2010; Schunk & Pajares, 2008). Further, there is a growing body of literature suggesting the need to engage students in mathematical modeling for instilling 21st century workforce skills (English & Sriraman, 2010; Kaiser, Blum, Ferri, & Stillman, 2011; Lesh & Doerr, 2003). In contrast to word problems usually found in school mathematics, solutions to modeling problems situated in real-world contexts are not readily available (Lesh, Yoon, & Zawojewski, 2007; Verschaffel, van Dooren, Greer, & Mukhopadhyay, 2010). To correctly solve modeling problems, students need to understand the context of the situation, select or acquire appropriate mathematical concepts, procedures and problem-solving strategies for describing the situation and interpreting the solution (Blum, 2011; Verschaffel et al., 2010). As a result, it would not be appropriate to measure students' self-efficacy for modeling tasks by merely asking their confidence in solving these problems, which is the typical way of measuring self-efficacy beliefs for solving mathematical tasks. Bandura (2006) also argued that behavior is better predicted by measuring individuals'

self-efficacy beliefs for processes or actions needed to exhibit a particular behavior (e.g., modeling-task success). The development of a Modeling Self-Efficacy scale not only fulfilled this need but also contributed to the growing literature of self-efficacy theory and mathematical modeling field. The data also provided evidence for the reliability and construct validity of the scale suggesting its use for future research purposes.

Implications

The present study found high correlations between the metacognitive self-regulation scale and the observed indicators for the cognitive strategy scale such as elaboration ($r = .876, p < .001$), critical thinking ($r = .730, p < .001$), and organization ($r = .716, p < .001$) subscales. The high multicollinearity found between the cognitive and metacognitive strategies indicated that the two scales might be measuring a similar construct. Therefore, one of the major theoretical implications of this study is that the measurement of cognitive and metacognitive constructs might not be easy for researchers. Artzt and Armour-Thomas (1992) also indicated that although cognitive and metacognitive activities can be distinguished conceptually but “operationally the distinction is often blurred” (p. 141). This is because metacognitive activities involve controlling, monitoring, and regulating cognitive processes, and cognitive activities such as the use of elaboration, organization, and critical thinking strategies may implicitly involve the use of metacognitive actions. As a result, it is difficult to categorize a particular problem-solving behavior as purely cognitive or purely metacognitive. For these reasons, Artzt and Arthur-Thomas advocate for observing students during small-group problem solving. The small-group problem solving not only provides natural settings for activating cognitive and metacognitive strategies but also offers researchers

with opportunities to differentiate problem-solving behaviors into cognitive and metacognitive activities through students' justifications of their own actions.

The present study also has some practical implications for the educators. The study provided evidence that self-efficacy is an important factor impacting students' performance in solving modeling tasks. Students' confidence in their own competence influences the amount of effort and time they expend (Schunk & Pajares, 2008). Therefore, teachers should support students in raising their self-efficacy beliefs for solving complex modeling problems. The self-efficacy literature, especially that stems from Bandura's social cognitive theory, offers several suggestions for raising students' self-efficacy beliefs for solving modeling tasks.

As peer relationships become increasingly important in adolescence (Schunk & Meece, 2006), teachers may provide students with vicarious learning experiences to raise their self-efficacy beliefs. Specifically, creating opportunities to observe peers with similar or higher ability levels struggle and eventually succeed when engaged in cognitively demanding modeling problems may motivate students to exert significant effort, time, and energy towards understanding and solving modeling problems.

Instructional practices such as providing students with effective feedback and engaging them in self-evaluative processes may also raise students' self-efficacy beliefs (Schunk & Mullen, 2012). Teacher feedback intended to encourage and make students aware of their capabilities supports them in believing themselves capable of solving complex modeling tasks. This is because students doubt their own competencies and hearing positive performance-related statements from teachers or their peers provide them with information about how well they are learning and performing on these tasks.

In addition to performance feedback, teachers should provide students with attribution feedback encouraging them to attribute their success to effort and failure to lack of effort. This would motivate students with low abilities to work harder and persist longer on academic tasks. Further, teachers should educate students to self-reflect, self-monitor, and self-evaluate their solution processes (Schunk & Ertmer, 2000; Schunk & Pajares, 2008). Such metacognitive processes may convey information about students' own learning progress, which further motivates them to persist at tasks and more cognitively engage in them. Furthermore, creating positive and supportive learning environments such as encouraging students to participate in classroom discussions, explaining their thought processes, and focusing on the process rather than the correct answer may positively impact students' self-efficacy beliefs.

Delimitations and Limitations of the Study

This study is delimited in several ways. First, SRL processes in the present study are limited to self-efficacy beliefs and cognitive and metacognitive strategy use. According to the model of self-regulation of learning proposed by Zimmerman and Campillo (2003), effective problem solvers engage in several self-regulatory processes such as goal setting, strategic planning, self-control, self-observation, self-judgment, and self-reaction processes, and they exhibit a variety of motivational beliefs such as self-efficacy, outcome expectation, task value, and goal orientation. Although all these variables are important, inclusion of too many variables in the statistical model would have been difficult to study and manage. Additionally, considering too many variables reduces the efficiency of a statistical model as it results in over fitting of a model with the sample data (Kline, 2005). The definition of cognitive strategy use was also delimited to self-reported use of elaboration, organization, and critical thinking strategies. The use of

rehearsal strategies such as naming, reciting, or repeating material for learning was deliberately excluded as these strategies were not identified in prior literature as effective in helping students understand complex modeling problems.

Second, the definition of mathematical modeling taken up in this study is somewhat limited. According to Julie (2002), there are two approaches to the teaching of mathematical modeling: modeling as vehicle and modeling as content. The modeling as vehicle approach uses mathematical modeling activities as a platform for teaching curriculum-based mathematical knowledge and skills. The primary purpose of this approach is to enhance students' understanding of a particular content area by using real-world contexts. The modeling as content approach, which is also the focus of the present study, involves the process of solving problems arising in other discipline areas or in real-world environments by making use of curriculum-based mathematics. This approach was appropriate for the present investigation as it was interested in examining factors that may influence students' ability to apply mathematical knowledge and skills in solving modeling problems. The Standards for Mathematical Practice also utilize modeling as content approach to exemplify the modeling expectations. Specifically, modeling practice requires students to apply mathematical concepts to understand problems situated in real-world contexts. Further, the present study focused on the extent to which students can utilize school-based knowledge and skills to solve real-world problems that students might find in their personal life, work, and leisure. Thus, this definition of mathematical modeling may be limited in promoting the essential 21st century skills and abilities.

Students' self-reported use of cognitive and metacognitive strategies was measured through the MSLQ questionnaire. By adopting the modeling perspective put forth by the Standards for Mathematical Practice (CCSSO, 2010), the focus of this study was to examine the extent to which students use and apply learning strategies acquired in schools to solve problems situated in real-world contexts. Therefore, the MSLQ scale, which measured students' use of cognitive and metacognitive strategies during school-based mathematical tasks, was considered appropriate.

Fourth, the present study engaged eighth- and ninth-grade students between 13 and 15 years of age. The PISA problems, however, were specifically designed for tenth-grade students between 15 to 16 years of age (OECD, 2004). This decision was made because think-aloud interviews conducted during the pilot study indicated that PISA problems were not challenging for tenth-grade students aged 15 to 18 years of age. This may have been the case because the study was conducted in a research developmental school where students are regularly engaged in innovative educational projects. Further, there is evidence when students are engaged in think-aloud interviews, they are more likely to provide correct responses to real-world challenging tasks (Selter, 1994, 2001). This is because interview questions, such as what exactly are you doing or why are you doing it, prompt students to reflect on their problem procedures and solutions. As a result, students may be more likely to provide correct responses.

The study has some limitations that need to be acknowledged. First, a limitation of any correlational research study is that correlations between two or more variables cannot be interpreted in terms of causal relationships. For example, the present study

suggests that there is a relationship between self-efficacy beliefs and students' performance on the modeling tasks, but the findings do not indicate a causal relationship between increased self-efficacy beliefs and correct modeling solutions. Second, data were collected using self-report questionnaires. Although survey methods are helpful in collecting large amounts of data in a relatively short period of time, there is an underlying assumption that participants provide honest responses to survey questions. The tendency of some participants to provide socially desirable responses might have introduced bias into the results. Third, the present study found low reliability estimate for the organization subscale ($\alpha = .61$) although prior studies (e.g., Kaya, 2007) reported this subscale to have good internal consistency ($\alpha = .72$). The low reliability index might indicate that the organization strategy subscale is not a reliable measure, but in the present study it might be an issue of sample size.

Further, the modeling test included problems adapted from the PISA 2003 problem-solving assessment. These problems were situated within the real-life contexts as well as embedded within the subject-areas of mathematics, science, and reading (OECD, 2004). The performance on the modeling test might be influenced by students' individual differences in reading, cognitive ability, their familiarity with the context of the problem, socioeconomic status, gender, and their prior mathematics achievement. The present study did not control for the influence of these factors on students' modeling achievement.

Summary. The main objective of this study was to examine the influence of self-efficacy beliefs and use of cognitive and metacognitive strategies on students' performance in solving modeling tasks. The findings of the present study provide

evidence that students' self-efficacy beliefs are significantly associated with modeling task success. The study, however, did not provide evidence for the direct influence of SRL strategy use on correctly solving modeling tasks. Further, the structural model did not provide evidence for the indirect influence of self-efficacy beliefs mediated by SRL strategy use on modeling task success. Future researchers might consider modifying the PISA scoring rubric to capture the range of mathematical skills displayed by students. This may result in increasing the reliability of the modeling test. They might modify the MSLQ scale involving revision of items with respect to real-life problem solving. Finally, they should consider giving these problems to tenth-grade students between 15 to 16 years of age.

APPENDIX A
THE MODELING TEST

(a) DECISION-MAKING TASKS

1. CINEMA OUTING

James, a 15 year old, wants to organize a cinema outing with two of his friends, who are of the same age, during the one-week Spring Break. The break begins on Saturday, March 24th and ends on Sunday, April 1st.

James asks his friends for suitable dates and times for the outing. He received the following information.

Mike: *"I have to stay home on Monday and Wednesday afternoons for music practice between 2:30 and 3:30."*

Richard: *"I have to visit my grandmother on Sundays, so it can't be Sundays. I have seen Tower Heist and don't want to see it again."*

James' parents insist that he only goes to movies suitable for his age and does not walk home. They will fetch the boys home at any time up to 10 p.m.

James checks the movie times for the Spring Break. He finds the following information.

Regal Cinema	
3702 West University Avenue, Gainesville FL-32607 Advance Booking Number: (352) 373-4277 Bargain Day Tuesdays: All films \$3 Films showing from Friday March 23rd for two weeks:	
Children in the Net 1hr and 53 min 2:00 PM (Mon-Fri only) 9:35 PM (Sat/Sun only) Suitable only for persons of 12 years and over	Pokamin 1 hr and 45 min 1:40 PM (Daily) 4:35 PM (Daily) Parental Guidance. General viewing, but some scenes may be unsuitable for young children
Monsters from the Deep 2 hrs and 44 min	Enigma 2 hrs and 24 min

7:55 PM (Fri/Sat only) Suitable only for persons of 18 years and over	3:00 PM (Mon-Fri only) 6:00 PM (Sat/Sun only) Suitable for persons of 12 years and over
Carnivore 2 hrs and 28 min 6:30 PM (Daily) Suitable only for persons of 18 years and over	King of the Wild 1 hr and 3 minutes 6:30 PM (Mon-Fri only) 6:50 PM (Sat/Sun only) Suitable for persons of all ages

Question 1: CINEMA OUTING

Taking into account the information James found on the movies, and the information he got from his friends, which of the six movies should James and the boys consider watching?

Circle “Yes/No” for each movie. Justify your responses.

Movie	Should the three boys consider watching the movie?
Children in the Net	Yes/No
Monsters from the Deep	Yes/No
Carnivore	Yes/No
Pokamin	Yes/No
Enigma	Yes/No
King of the Wild	Yes/No

2. ENERGY NEEDS

This problem is about selecting suitable food to meet the energy needs of a person in Florida. The following table shows the recommended energy needs in kilojoules (KJ) for different people.

DAILY ENERGY NEEDS RECOMMENDED FOR ADULTS

Age (years)	Activity Level	MEN	WOMEN
		Energy Needed (KJ)	Energy Needed (KJ)
From 18 to 29	Light	10660	8360
	Moderate	11080	8780
	Heavy	14420	9820
From 30 to 59	Light	10450	8570
	Moderate	12120	8990
	Heavy	14210	9790
60 and above	Light	8780	7500
	Moderate	10240	7940
	Heavy	11910	8780

ACTIVITY LEVEL ACCORDING TO OCCUPATION

Light	Moderate	Heavy
Indoor sales person	Teacher	Construction worker
Office worker	Outdoor salesperson	Laborer
Housewife	Nurse	Sportsperson

Samantha Gibbs is a 19-year old high jumper. One evening, some of Samantha's friends invite her out for dinner at a restaurant. Here is the menu.

<i>MENU</i>		Samantha's estimate of energy per serving (KJ)
Soups:	Tomato Soup	355
	Cream of Mushroom Soup	585
Main Courses:	Mexican Chicken	960
	Caribbean Ginger Chicken	795
	Pork and Sage Kebabs	920
Salads:	Potato Salad	750
	Spinach, Apricot and Hazelnut Salad	335
	Couscous Salad	480
Desserts:	Apple and Raspberry Crumble	1380
	Ginger Cheesecake	1005
	Carrot Cake	565

Milk Shakes:	Chocolate	1590
	Vanilla	1470

The restaurant also has a special fixed price menu.

Fixed Price Menu (50 dollars) Tomato Soup Caribbean Ginger Carrot Cake
--

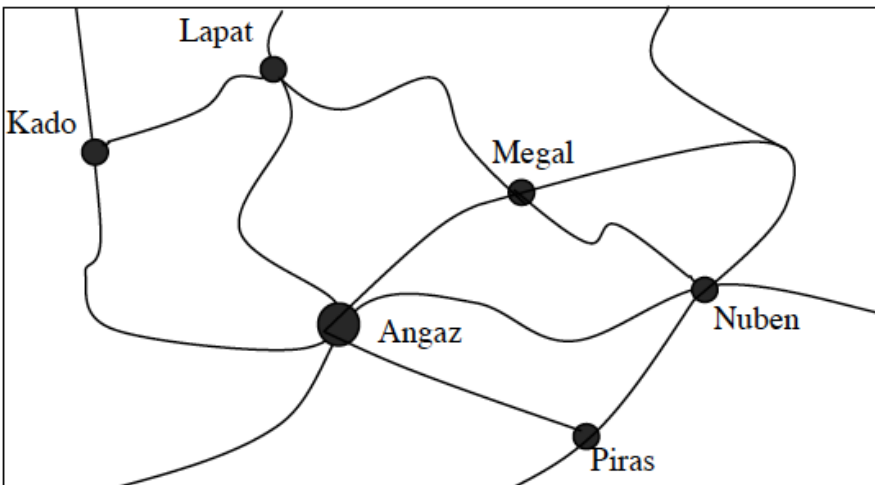
QUESTION 2: ENERGY NEEDS

Samantha keeps a records of what she eats each day. Before dinner on that day her total intake of energy had been 7520 kJ. Samantha does **not** want her total energy intake to go **below or above her recommended daily amount** by more than 500 kJ.

Decide whether the special “Fixed Price Menu” will allow Samantha to stay within ± 500 kJ of her recommended energy needs. Show your work.

3. HOLIDAY

This problem is about planning the best route for a holiday.
s 1 and 2 show a map of the area and the distance between towns.



1: Map of roads between towns

Angaz						
Kado	550					
Lapat	500	300				
Megal	300	850	550			
Nuben	500		1000	450		
Piras	300	850	800	600	250	
	Angaz	Kado	Lapat	Megal	Nuben	Piras

QUESTION 3: HOLIDAY

Calculate the shortest distance by road between Nuben and Kado.

Distance: _____ miles.

(b) SYSTEM ANALYSIS AND DESIGN TASKS

4. CHILDREN’S CAMP

The Florida Gator Community Service is organizing a five-day Children’s Camp. Forty-six children (26 girls and 20 boys) have signed up for the camp, and 8 adults (4 men and 4 women) have volunteered to attend and organize the camp.

Table 1: Adults

Mrs Madison
Mrs Carroll
Ms Grace
Ms Kelly
Mr Stevens
Mr Neill
Mr Williams
Mr Peters

Table 2: Dormitories

Name	Number of beds
Red	12
Blue	8
Green	8
Purple	8
Orange	8
Yellow	6
White	6

Dormitory rules:

1. Boys and girls must sleep in separate dormitories.
2. At least one adult must sleep in each dormitory.
3. The adult(s) in a dormitory must be of the same gender as the children.

QUESTION 4: CHILDREN'S CAMP

Dormitory Allocation.

Fill the table to allocate the 46 children and 8 adults to dormitories, keeping to all the rules

Name	# of Boys	# of girls	Name(s) of adult(s)
Red			
Blue			
Green			
Purple			
Orange			
Yellow			
White			

5. COURSE DESIGN

A technical college offers the following 12 subjects for a 3-year course, where the length of each subject is one year.

	Subject Code	Subject Name
1	M1	Mechanics Level 1
2	M2	Mechanics Level 2
3	E1	Electronics Level 1
4	E2	Electronics Level 2
5	B1	Business Studies Level 1
6	B2	Business Studies Level 2
7	B3	Business Studies Level 3
8	C1	Computer Systems Level 1
9	C2	Computer Systems Level 2
10	C3	Computer Systems Level 3
11	T1	Technology and Information Management Level 1
12	T2	Technology and Information Management Level 2

QUESTION 5: COURSE DESIGN

Each student will take 4 subjects per year, thus completing 12 subjects in 3 years.

A student can only take a subject at a higher level if the student has completed the lower level(s) of the same subject in a previous year. For example, you can only take Business Studies Level 3 after completing Business Studies Levels 1 and 2.

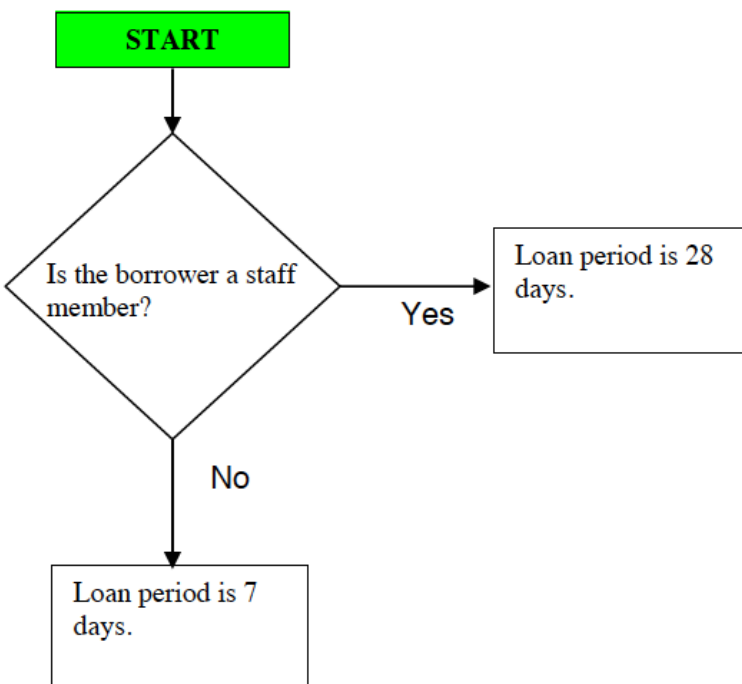
In addition, Electronics Level 1 can only be taken after completing Mechanics Level 1, and Electronics Level 2 can only be taken after completing Mechanics Level 2.

Decide which subjects should be offered for which year, by completing the following table. Write the subject codes in the table.

	Subject 1	Subject 2	Subject 3	Subject 4
Year 1				
Year 2				
Year 3				

6. LIBRARY SYSTEM

The **John Hobson High School** library has a simple system for lending books: for staff members the loan period is 28 days, and for students the loan period is 7 days. The following is a decision tree diagram showing this simple system:



The **Greenwood High School** library has a similar, but more complicated, lending system:

- All publications classified as “Reserved” have a loan period of 2 days.
- For books (not including journals) that are **not** on the reserved list, the loan period is 28 days for staff, and 14 days for students.
- For journals that are **not** on the reserved list, the loan period is 7 days for everyone.
- Persons with any overdue items are not allowed to borrow anything.

QUESTION 6: LIBRARY SYSTEM

You are a student at **Greenwood High School**, and you do not have any overdue items from the library. You want to borrow a book that is **not** on the reserved list. How long can you borrow the book for?

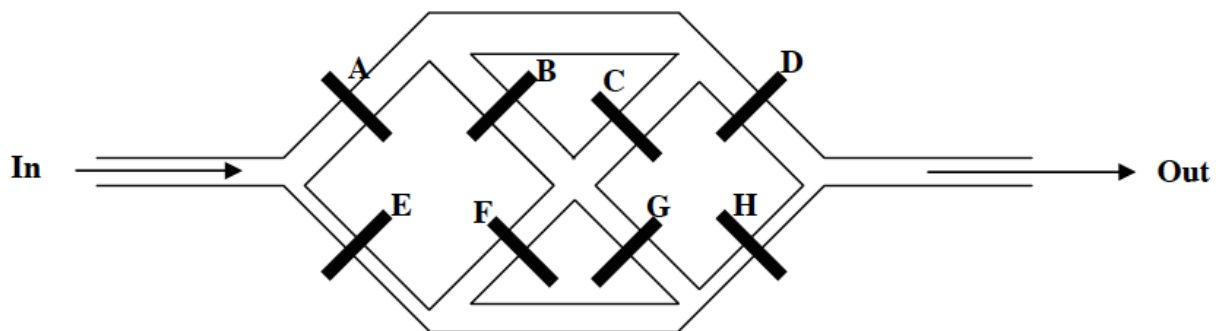
Answer: _____ days

(c) TROUBLESHOOTING TASKS

7. IRRIGATION

Below is a diagram of a system of irrigation channels for watering sections of crops. The gates A to H can be opened and closed to let the water go where it is needed. When a gate is closed no water can pass through it.

This is a problem about finding a gate, which is stuck closed, preventing water from flowing through the system of channels.



Michael notices that the water is not always going where it is supposed to. He thinks that one of the gates is stuck closed, so that when it is switched to open, it does not open.

QUESTION 7: IRRIGATION

Michael used the following gate settings to test the gates.

Table 1: Gate Settings

A	B	C	D	E	F	G	H
Open	Closed	Open	Open	Closed	Open	Closed	Open

Michael finds that, when the gates have the Table 1 settings, no water flows through, indicating that at least one of the gates set to “open” is stuck closed.

Decide for each problem case below whether the water will flow through all the way. Circle “Yes” or “No” in each case, and **justify** your response.

Problem Case	Will water flow through all the way?
Gate A is stuck closed. All other gates are working properly as set in Table 1.	YES / NO
Gate D is stuck closed. All other gates are working properly as set in Table 1.	YES / NO
Gate F is stuck closed. All other gates are working properly as set in Table 1.	YES / NO

8. FREEZER

Jane bought a new cabinet-type freezer. The manual gave the following instructions:

- Connect the appliance to the power and switch the appliance on.
 - You will hear the motor running now.
 - A red warning light (LED) on the display will light up.
- Turn the temperature control to the desired position. Position 2 is normal.

Position	Temperature
1	5°F
2	-0.399°F
3	-5.80°F
4	-13°F
5	-25.6°F

The red warning light will stay on until the freezer temperature is low enough. This will take 1-3 hours, depending on the temperature you set.

- Load the freezer with food after four hours.

Jane followed these instructions, but she set the temperature control to position 4. After 4 hours, she loaded the freezer with food. After 8 hours, the red warning light was still on, although the motor was running and it felt cold in the freezer.

QUESTION 8: FREEZER

Jane wondered whether the warning light was functioning properly. Which of the following actions and observations would suggest that the light was working properly?

Circle "Yes" or "No" for each of the three cases.

Action and Observation	Does the observation suggest that the warning light was working properly?
She put the control to position 5 and the red light went off.	Yes / No
She put the control to position 1 and the red light went off.	Yes / No
She put the control to position 1 and the red light stayed on.	Yes / No

9. HOSPITAL

The cardiology department at a local hospital employs 5 doctors. Every doctor can work from Monday to Friday and examine 10 patients per day. In a whole year (365 days, 52 weeks) a cardiologist can have 25 days for holidays, and 26 days off for attending seminars and the weekends.

QUESTION 9: Can the 5 cardiologists deal with the 12000 patients that are expected to arrive at the hospital during the following year? If not, what do you suggest that the hospital can do? Explain your answer.

APPENDIX B
SELF-EFFICACY SCALE

The following scale will be used to measure students' self-efficacy related to each problem on the modeling ability test. Students will read each problem and respond to following questions on a scale ranging from 0 to 100.

1. How sure are you that you can understand this mathematical problem?

0	10	20	30	40	50	60	70	80	90	100
Not at all Sure			Moderately Sure					Very Sure		

2. How sure are you that you can determine a strategy to solve this problem?

0	10	20	30	40	50	60	70	80	90	100
Not al all sure			Moderately Sure					Very Sure		

3. How sure are you that you can determine the information required to solve this problem?

0	10	20	30	40	50	60	70	80	90	100
Not at all Sure			Moderately Sure					Very Sure		

4. How sure are you that you can solve this mathematical problem correctly?

0	10	20	30	40	50	60	70	80	90	100
Not at all Sure			Moderately sure					Very Sure		

APPENDIX C
MOTIVATED STRATEGIES FOR LEARNING QUESTIONNAIRE

Today's Date: _____

Participant Number: _____

Student's Initials: _____

Month of birth: _____

Year of birth: _____

Grade in school: _____

Gender: Male Female

Ethnicity: American Indian
 Asian
 Black or African-American
 Hispanic or Latino/a
 Native Hawaiian or Pacific Islander
 White, non-Hispanic
 Other (please specify)

The following questions ask about your learning strategies and study skills for YOUR mathematics class. When the questions ask you about *the readings for the class* think about reading the textbook that you have for your mathematics class or other materials your teacher might give you to read or study from.

Again, there are no right or wrong answers. Answer the questions about how you study in this class as accurately as possible. Use the same scale to answer the remaining questions. If you think the statement is **very true** of you, fill in the circle next to 7; if a statement is **not at all true** of you, fill in the circle next to 1. If the statement is **more or less true of you**, find the number between 1 and 7 that best describes you.

Not at all true 1 2 3 4 5 6 7 **Very true of me**

Motivated Strategies for Learning Questionnaire

		<i>Not at all true</i>						<i>Very true of me</i>
1.	When I study the readings (your mathematics textbook) for this course, I outline the material to help me organize my thoughts.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
2.	I often find myself questioning things I hear or read in this course to decide if I find them convincing.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
3.	When I become confused about something I'm reading for this class, I go back and try to it out.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
4.	When I study for this course, I go through the readings (your mathematics textbook) and my class notes and try to find the most important ideas.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
5.	If course readings (your mathematics textbook) are difficult to understand, I change the way I read the material.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
6.	When a theory, interpretation, or conclusion is presented in class or in the readings (your mathematics textbook), I try to decide if there is good supporting evidence.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
7.	I make simple charts, diagrams, or tables to help me organize course material.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
8.	I treat the course material as a starting point and try to develop my own ideas about it.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
9.	When I study for this class, I pull together information from different sources, such as lectures, readings (your mathematics textbook), and discussions we have in class.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
10.	Before I study new course material thoroughly, I often skim it to see how it is organized.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
11.	I ask myself questions to make sure I understand the material I have been studying in this class.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
12.	I try to change the way I study in order	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

	to fit the course requirements and the way my teacher presents the material.	
13.	I try to think through a topic and decide what I am supposed to learn from it rather than just reading it over when studying for this course.	O 1 O 2 O 3 O 4 O 5 O 6 O 7
14.	I try to relate ideas in this subject to those in other courses whenever possible.	O 1 O 2 O 3 O 4 O 5 O 6 O 7
15.	When I study for this course, I go over my class notes and make an outline of important concepts.	O 1 O 2 O 3 O 4 O 5 O 6 O 7
16.	When reading (your mathematics textbook) for this class, I try to relate the material to what I already know.	O 1 O 2 O 3 O 4 O 5 O 6 O 7
17.	I try to play around with ideas of my own related to what I am learning in this course.	O 1 O 2 O 3 O 4 O 5 O 6 O 7
18.	When I study for this course, I write brief summaries of the main ideas from the readings (your mathematics textbook) and my class notes.	O 1 O 2 O 3 O 4 O 5 O 6 O 7
19.	I try to understand the material in this class by making connections between the readings (your mathematics textbook) and the concepts from my teachers' lectures.	O 1 O 2 O 3 O 4 O 5 O 6 O 7
20.	Whenever I read or hear an assertion or conclusion in this class, I think about possible alternatives.	O 1 O 2 O 3 O 4 O 5 O 6 O 7
21.	When studying for this course I try to determine which concepts I don't understand well.	O 1 O 2 O 3 O 4 O 5 O 6 O 7
22.	When I study for this class, I set goals for myself in order to direct my activities in each study period.	O 1 O 2 O 3 O 4 O 5 O 6 O 7
23.	If I get confused taking notes in class, I make sure I sort it out afterwards.	O 1 O 2 O 3 O 4 O 5 O 6 O 7
24.	I try to apply ideas from course readings (your mathematics textbook) in other class activities such as lecture and discussion.	O 1 O 2 O 3 O 4 O 5 O 6 O 7

APPENDIX D
THE MODELING TEST

(a) DECISION-MAKING TASKS

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Carnivore 2 hrs and 28 min 6:30 PM (Daily) Suitable only for persons of 18 years and over	King of the Wild 1 hr and 3 minutes 6:30 PM (Mon-Fri only) 6:50 PM (Sat/Sun only) Suitable for persons of all ages

Question 1: CINEMA OUTING

Taking into account the information James found on the movies, and the information he got from his friends, which of the six movies should James and the boys consider watching?

Circle "Yes/No" for each movie. Justify your responses.

Movie	Should the three boys consider watching the movie?
Children in the Net	Yes/No
Monsters from the Deep	Yes/No
Carnivore	Yes/No
Pokamin	Yes/No
Enigma	Yes/No
King of the Wild	Yes/No

2. ENERGY NEEDS

This problem is about selecting suitable food to meet the energy needs of a person in Florida. The following table shows the recommended energy needs in kilojoules (KJ) for different people.

DAILY ENERGY NEEDS RECOMMENDED FOR ADULTS

Age (years)	Activity Level	MEN	WOMEN
		Energy Needed (KJ)	Energy Needed (KJ)
From 18 to 29	Light	10660	8360
	Moderate	11080	8780
	Heavy	14420	9820
From 30 to 59	Light	10450	8570
	Moderate	12120	8990
	Heavy	14210	9790
60 and above	Light	8780	7500
	Moderate	10240	7940
	Heavy	11910	8780

ACTIVITY LEVEL ACCORDING TO OCCUPATION

Light	Moderate	Heavy
Indoor sales person	Teacher	Construction worker
Office worker	Outdoor salesperson	Laborer
Housewife	Nurse	Sportsperson

Samantha Gibbs is a 19-year old high jumper. One evening, some of Samantha's friends invite her out for dinner at a restaurant. Here is the menu.

<i>MENU</i>		Samantha's estimate of energy per serving (KJ)
Soups:	Tomato Soup	355
	Cream of Mushroom Soup	585
Main Courses:	Mexican Chicken	960
	Caribbean Ginger Chicken	795
	Pork and Sage Kebabs	920
Salads:	Potato Salad	750
	Spinach, Apricot and Hazelnut Salad	335
	Couscous Salad	480
Desserts:	Apple and Raspberry Crumble	1380
	Ginger Cheesecake	1005
	Carrot Cake	565

Milk Shakes:	Chocolate	1590
	Vanilla	1470

The restaurant also has a special fixed price menu.

<p>Fixed Price Menu (50 dollars) Tomato Soup Caribbean Ginger Carrot Cake</p>
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QUESTION 2: ENERGY NEEDS

Samantha keeps a records of what she eats each day. Before dinner on that day her total intake of energy had been 7520 kJ. Samantha does **not** want her total energy intake to go **below or above her recommended daily amount** by more than 500 kJ.

Decide whether the special “Fixed Price Menu” will allow Samantha to stay within ± 500 kJ of her recommended energy needs. Show your work.

(b) SYSTEM ANALYSIS AND DESIGN TASKS

3. CHILDREN’S CAMP

The Florida Gator Community Service is organizing a five-day Children’s Camp. Forty-six children (26 girls and 20 boys) have signed up for the camp, and 8 adults (4 men and 4 women) have volunteered to attend and organize the camp.

Table 1: Adults

Mrs Madison
Mrs Carroll
Ms Grace
Ms Kelly
Mr Stevens
Mr Neill
Mr Williams
Mr Peters

Table 2: Dormitories

Name	Number of beds
Red	12
Blue	8
Green	8
Purple	8
Orange	8
Yellow	6
White	6

Dormitory rules:

1. Boys and girls must sleep in separate dormitories.
2. At least one adult must sleep in each dormitory.
3. The adult(s) in a dormitory must be of the same gender as the children.

QUESTION 3: CHILDREN'S CAMP

Dormitory Allocation.

Fill the table to allocate the 46 children and 8 adults to dormitories, keeping to all the rules

Name	# of Boys	# of girls	Name(s) of adult(s)
Red			
Blue			
Green			
Purple			
Orange			
Yellow			
White			

4. COURSE DESIGN

A technical college offers the following 12 subjects for a 3-year course, where the length of each subject is one year.

	Subject Code	Subject Name
1	M1	Mechanics Level 1
2	M2	Mechanics Level 2
3	E1	Electronics Level 1
4	E2	Electronics Level 2
5	B1	Business Studies Level 1
6	B2	Business Studies Level 2
7	B3	Business Studies Level 3
8	C1	Computer Systems Level 1
9	C2	Computer Systems Level 2
10	C3	Computer Systems Level 3
11	T1	Technology and Information Management Level 1
12	T2	Technology and Information Management Level 2

QUESTION 4: COURSE DESIGN

Each student will take 4 subjects per year, thus completing 12 subjects in 3 years.

A student can only take a subject at a higher level if the student has completed the lower level(s) of the same subject in a previous year. For example, you can only take Business Studies Level 3 after completing Business Studies Levels 1 and 2.

In addition, Electronics Level 1 can only be taken after completing Mechanics Level 1, and Electronics Level 2 can only be taken after completing Mechanics Level 2.

Decide which subjects should be offered for which year, by completing the following table. Write the subject codes in the table.

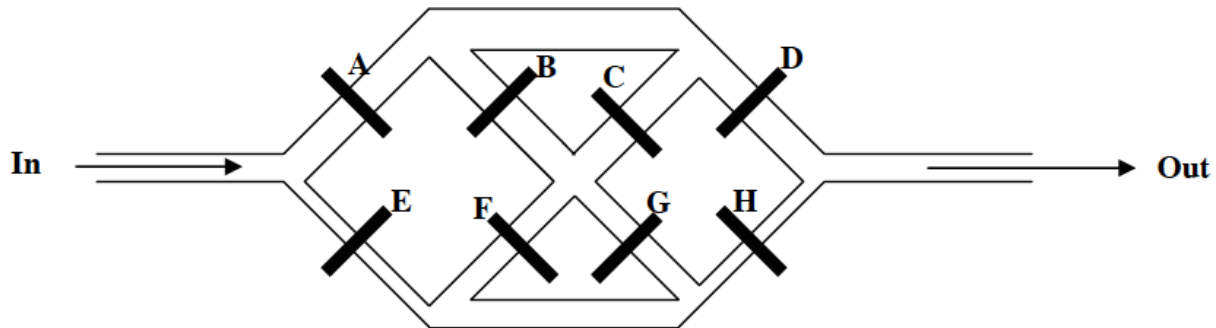
	Subject 1	Subject 2	Subject 3	Subject 4
Year 1				
Year 2				
Year 3				

(c) TROUBLESHOOTING TASKS

5. IRRIGATION

Below is a diagram of a system of irrigation channels for watering sections of crops. The gates A to H can be opened and closed to let the water go where it is needed. When a gate is closed no water can pass through it.

This is a problem about finding a gate, which is stuck closed, preventing water from flowing through the system of channels.



Michael notices that the water is not always going where it is supposed to. He thinks that one of the gates is stuck closed, so that when it is switched to open, it does not open.

QUESTION 5: IRRIGATION

Michael used the following gate settings to test the gates.

Table 1: Gate Settings

A	B	C	D	E	F	G	H
Open	Closed	Open	Open	Closed	Open	Closed	Open

Michael finds that, when the gates have the Table 1 settings, no water flows through, indicating that at least one of the gates set to “open” is stuck closed.

Decide for each problem case below whether the water will flow through all the way. Circle “Yes” or “No” in each case, and **justify** your response.

Problem Case	Will water flow through all the way?
Gate A is stuck closed. All other gates are working properly as set in Table 1.	YES / NO
Gate D is stuck closed. All other gates are working properly as set in Table 1.	YES / NO
Gate F is stuck closed. All other gates are working properly as set in Table 1.	YES / NO

6. FREEZER

Jane bought a new cabinet-type freezer. The manual gave the following instructions:

- Connect the appliance to the power and switch the appliance on.
 - You will hear the motor running now.
 - A red warning light (LED) on the display will light up.
- Turn the temperature control to the desired position. Position 2 is normal.

Position	Temperature
1	5°F
2	-0.399°F
3	-5.80°F
4	-13°F
5	-25.6°F

The red warning light will stay on until the freezer temperature is low enough. This will take 1-3 hours, depending on the temperature you set.

- Load the freezer with food after four hours.

Jane followed these instructions, but she set the temperature control to position 4. After 4 hours, she loaded the freezer with food. After 8 hours, the red warning light was still on, although the motor was running and it felt cold in the freezer.

QUESTION 6: FREEZER

Jane wondered whether the warning light was functioning properly. Which of the following actions and observations would suggest that the light was working properly?

Circle “Yes” or “No” for each of the three cases.

Action and Observation	Does the observation suggest that the warning light was working properly?
She put the control to position 5 and the red light went off.	Yes / No
She put the control to position 1 and the red light went off.	Yes / No
She put the control to position 1 and the red light stayed on.	Yes / No

APPENDIX E
SCORING RUBRIC FOR MODELING PROBLEMS

1. CINEMA OUTING SCORING

Full Credit (Score 2)	Partial Credit (Score 1)	No Credit (Score 0)
If the answers are in the order: Yes, No, No, No, Yes and Yes	One incorrect answer	Other responses

2. ENERGY NEEDS SCORING

Full Credit (Score 2)	Partial Credit (Score 1)	No Credit (Score 0)
<p>Food from the fixed price menu does not contain enough energy for Samantha to keep within 500 KJ of her energy needs. The following steps are necessary:</p> <p>(i) Calculation of the total energy of the fixed price menu: $355+795+565=1715$</p> <p>(ii) Recognition that Samantha’s daily recommended energy need is 9820 KJ.</p> <p>(iii) Calculating $7520+1715=9235$ and showing that Samantha would be more than 500 KJ below her recommended energy need.</p> <p>(iv) Conclusion that the fixed price menu does not contain enough energy.</p>	<p>Correct method, but a minor error or omission in one of the calculation steps leading to a correct or incorrect, but consistent, conclusion.</p> <ul style="list-style-type: none"> $1715+7520=9235$, this is within 500 of 8780, so “Yes” <p>Or</p> <p>Correct calculations, but concludes “Yes” or gives no conclusion</p>	<p>Other responses, including “No” without explanation.</p> <ul style="list-style-type: none"> No, Samantha should not order from the fixed price menu 1715 is above 500 KJ, so Samantha should not have this <p>Or</p> <p>Correct reasoning in words but no s shown. That is partial credit needs to have some supporting s.</p> <ul style="list-style-type: none"> The fixed price menu does not have enough KJ, so Samantha should not have it.

3. CHILDREN’S CAMP SCORING

Full Credit (Score 2)	Partial Credit (Score 1)	No Credit (Score 0)
<p>Six conditions to be satisfied</p> <ul style="list-style-type: none"> Total girls = 26 Total boys = 20 	<p>One or two conditions (as mentioned in the first column) violated. Violating the same condition more than once will</p>	<p>Other responses.</p>

<ul style="list-style-type: none"> • Total adults = four female and four male • Total (children and adults) per dormitory is within the limit for each dormitory. • People in each dormitory are of the same gender. • At least one adult must sleep in each dormitory to which children have been allocated. 	<p>be counted as ONE violation only.</p> <ul style="list-style-type: none"> • Forgetting to count the adults in the tally of the number of people in each dormitory. • The number of girls and the number of boys are interchanged (no. of girls = 20, no. of boys = 26), but everything else is correct. (Note that this counts as two conditions violated) • The correct number of adults in each dormitory is given, but not their names or gender. (Note that this violates both condition 3 and condition 5). 	
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5. COURSE DESIGN SCORING

Full Credit (Score 2)	Partial Credit (Score 1)	No Credit (Score 0)																				
<p>The order of subjects within a year is unimportant, but the list of subjects for each year should be as given below:</p> <table border="1" data-bbox="191 1291 688 1444"> <thead> <tr> <th></th> <th>Sub1</th> <th>Sub2</th> <th>Sub3</th> <th>Sub4</th> </tr> </thead> <tbody> <tr> <td>Y1</td> <td>B1</td> <td>M1</td> <td>T1</td> <td>C1</td> </tr> <tr> <td>Y2</td> <td>B2</td> <td>M2</td> <td>E1</td> <td>C2</td> </tr> <tr> <td>Y3</td> <td>B3</td> <td>T2</td> <td>E2</td> <td>C3</td> </tr> </tbody> </table>		Sub1	Sub2	Sub3	Sub4	Y1	B1	M1	T1	C1	Y2	B2	M2	E1	C2	Y3	B3	T2	E2	C3	<p>Mechanics does not precede electronics. All other constraints are satisfied.</p>	<p>Other responses</p> <p>Table completely correct except that “E2” is missing and “E1” is repeated where “E2” should be or this cell is empty.</p>
	Sub1	Sub2	Sub3	Sub4																		
Y1	B1	M1	T1	C1																		
Y2	B2	M2	E1	C2																		
Y3	B3	T2	E2	C3																		

5. IRRIGATION SCORING

Full Credit (Score 1)	No Credit (Score 0)
No, Yes, Yes in that order	Other responses

6. FREEZER SCORING

Full Credit (Score 1)	No Credit (Score 0)
No, Yes, No in that order	Other responses

LIST OF REFERENCES

- Allison, P. D. (2003). Missing data techniques for structural equation modeling. *Journal of Abnormal Psychology, 112*, 545-557.
- Arbuckle, J.L. (1996) Full information estimation in the presence of incomplete data. In G.A. Marcoulides & R.E. Schumacker (Eds.), *Advanced structural equation modeling: Issues and Techniques*. Mahwah, NJ: Lawrence Erlbaum Associates.
- Artzt, A. F., & Arthur-Thomas, E. (1992). Development of cognitive-metacognitive framework for protocol analysis of mathematical problem solving in small groups. *Cognition and Instruction, 9*, 137-175.
- Bandura, A. (1986). *Social foundations of thought and action*. Englewood Cliffs, NJ: Prentice Hall.
- Bandura, A. (1997). *Self-efficacy: the exercise of control*. New York: Freeman.
- Baraldi, A.N., & Enders, C.K. (2010). An introduction to modern missing data analyses. *Journal of School of Psychology, 48*, 5-37.
- Barbosa, J. C. (2010). The students' discussions in the modeling environment. In R. Lesh, P. L. Galbraith, C. R. Haines, & A. Hurford (Eds.), *Modeling students' mathematical modeling competencies* (pp. 365-372). New York: Springer.
- Bentler, P. M. (2005). *EQS 6 structural equations program manual*. Encino, CA: Multivariate Software.
- Blum, W. (2011). Can modeling be taught and learnt? Some answers from empirical research. In G. Kaiser, W. Blum, R. B. Ferri, & G. Stillman (Eds.), *Trends in teaching and learning of mathematical modeling* (pp. 15-30). New York: Springer.
- Bouffard-Bouchard, T., Parent, S., & Larivee, S. (1991). Influence of self-efficacy on self-regulation and performance among junior and senior high-school age students. *International Journal of Behavioral Development, 14*, 153–164.
- Bransford, J., & Stein, B. (1984). *The IDEAL problem solver*. New York: W. H. Freeman.
- Brown, T. A. (2006). *Confirmatory Factor Analysis for Applied Research*. New York: Guilford Press.
- Browne, M. W., & Cudeck, R. (1993). Alternative ways of assessing model fit. In K. A. Bollen & J. S. Long (Eds.), *Testing Structural Equation Models* (pp. 136–162). Beverly Hills, CA: Sage.
- Byrne, B. M. (2009). *Structural equation modeling with AMOS: Basic concepts, applications, and programming* (2nd ed.). New York, NY: Routledge.

- Byrne, B. M. (2012). *Structural equation modeling with Mplus: Basic concepts, applications, and programming*. New York, NY: Routledge.
- Carriera, S., Amado, N., & Lecoq, F. (2011). Mathematical modeling of daily life in adult education: Focusing on the notion of knowledge. In G. Kaiser, W. Blum, R. B. Ferri, & G. Stillman (Eds.), *Trends in teaching and learning of mathematical modeling* (pp. 199-210). New York: Springer.
- Chen, P. P. (2003). Exploring the accuracy and predictability of the self-efficacy beliefs of seventh-grade mathematics students. *Learning and individual differences, 14*, 79-92.
- 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*, 61-82.
- Cleary, T. J., & Zimmerman, B. J. (2012). A cyclical self-regulatory account of student engagement: Theoretical foundations and applications. In S. L. Christenson, A. L. Reschly, & C. Wylie (Eds.), *Handbook of research on student engagement* (pp. 237-258). New York: Springer.
- Collins, J. L. (1982). *Self-efficacy and ability in achievement behavior*. Paper presented at the meeting of the American Educational Research Association, New York.
- Council of Chief State School Officers (2010). *Common Core State Standards (Mathematics)*. Washington, DC: National Governors Association Centre for Best Practices.
- Dabbagh, N., & Kitsantas, A. (2004). Supporting self-regulation in student-centered Web-based learning environments. *International Journal on E-Learning, 3*, 40-47.
- Dark, M. J. (2003). A models and modeling perspective on skills for the high performance workplace. In R. Lesh and H. M. Doerr (Eds.), *Beyond constructivism: Models and modeling perspectives on mathematics problem solving, learning, and teaching* (pp. 279-295). Mahwah, NJ: Lawrence Erlbaum Associates.
- DeCarlo, L. T. (1997). On the meaning and use of kurtosis. *Psychological Methods, 2*, 292-307.
- De Corte, E., Verschaffel, L., & Op 't Eynde P. (2000). Self-regulation: A characteristic and a goal of mathematics education. In P. Pintrich, M. Boekaerts, & M. Zeidner (Eds.), *Self-regulation: Theory, research, and applications* (pp. 687-726). Mahwah, NJ: Lawrence Erlbaum Associates.
- Dignath, C., Buettner, G., & Langfeldt, H. P. (2008). How can primary school students learn self-regulated learning strategies most effectively: A meta-analysis of self-regulation training programmes. *Educational Research Review, 3*, 101-129.

- Doerr, H., & English, L. D. (2003). A modelling perspective on students' mathematical reasoning about data. *Journal for Research in Mathematics Education*, 34, 110-136.
- Enders, C.K. (2001). The impact of nonnormality on full information maximum likelihood estimation for structural equation models with missing data. *Psychological Methods*, 6, 352-370.
- English, L.D. (2006). Mathematical Modeling in the primary school. *Educational Studies in Mathematics*, 63, 303-323.
- English, L. D. (2011). Complex modeling in the primary/middle school years. In G. Stillman and J. Brown (Eds.), *ICTMA Book of Abstracts* (pp. 1-10). Australian Catholic University, Australian Catholic University, Melbourne, VIC.
- English, L. D., Lesh, R., & Fennewald, T. (2008). *Future directions and perspectives for problem solving research and curriculum development*. Paper presented at the 11th International Conference on Mathematical Education, 6-13 July 2008 in Monterrey, Mexico.
- English, L. D., & Sriraman, B. (2010). Problem solving for the 21st century. In B. Sriraman, & L. English (Eds.), *Theories of mathematics education: Seeking new frontiers* (pp. 263-290). New York: Springer.
- Eric, C. C. M. (2009). Mathematical modeling as problem solving for children in the Singapore mathematics classrooms. *Journal of Mathematics and Science*, 32, 36-61.
- Eric, C. C. M. (2010). Tracing primary 6 students' model development within the mathematical modeling process. *Journal of Mathematical Modeling and Applications*, 1, 40-57.
- Fabrigar, L. R., Wegener, D. T., MacCallum, R. C., & Strahan, E. J. (1999). Evaluating the use of exploratory factor analysis in psychological research. *Psychological Methods*, 4, 272-299.
- Galbraith, P. (2012). Models of modeling: Genres, purposes or perspectives. *Journal of Mathematical Modelling and Application*, 5, 3-16.
- Garcia, T., & Pintrich, P. R. (1994). Regulating motivation and cognition in the classroom: the role of self-schemas and self-regulatory strategies. In D. H. Schunk and B. J. Zimmerman (Eds.), *Self-regulation on learning and performance: Issues and Applications* (pp. 132 – 157). Hillsdale, NJ: Lawrence Erlbaum.
- Gonzales, P., Williams, T., Jocelyn, L., Roey, S., Kastberg, D., & Brenwald, S. (2008). *Highlights From TIMSS 2007: Mathematics and science achievement of U.S. fourth- and eighth-grade students in an international context* (National Center for

Education Statistics Publication No. 2009–001 Revised). Retrieved from National Center for Educational Statistics website:
<http://nces.ed.gov/pubsearch/pubsinfo.asp?pubid=2009001>

- Greene, B. A., Miller, R. B., Crowson, H. M., Duke, B. L., & Akey, K. L. (2004). Predicting high school students' cognitive engagement and achievement: Contributions of classroom perceptions and motivation. *Contemporary Educational Psychology, 29*, 462-482.
- Grewal, R., Cote, J. A., & Baumgartner, H. (2004). Multicollinearity and measurement error in structural equation models: Implications for theory testing. *Marketing Science, 23*, 519-529.
- Hair, J., Black, B. Babin, B., Anderson, R. & Tatham, R. (2006). *Multivariate Data Analysis* (6th ed.). Upper Saddle River, NJ: Prentice-Hall.
- Heidari, F., Izadi, M., & Ahmadian, M. (2012). The relationship between Iranian EFL learners' self-efficacy beliefs and use of vocabulary learning strategies. *English Language Teaching, 5*, 174-182.
- Hestenes, D. (2010). Modeling theory for math and science education. In R. Lesh, P. L. Galbraith, C. R. Haines, & A. Hurford (Eds.), *Modeling students' mathematical modeling competencies* (pp. 13-41). New York: Springer.
- Hoffman, B., & Spatariu, A. (2008). The influence of self-efficacy and metacognitive prompting on math problem-solving efficiency. *Contemporary Educational Psychology, 33*, 875-893.
- Hoyle, R. H. (1995). *Structural equation modeling: Concepts, issues, and applications*. Thousand Oaks, California: SAGE Publications.
- Jackson, D. L. (2001). Sample size and number of parameter estimates in maximum likelihood confirmatory factor analysis: A Monte Carlo investigation. *Structural Equation Modeling, 8*, 205–223.
- Jackson, D. L. (2003). Revisiting sample size and the number of parameter estimates: Some support for the n:q hypothesis. *Structural Equation Modeling: A multidisciplinary Journal, 10*, 128-141.
- Julie, C. (2002). Making relevance relevant in mathematics teacher education. Proceedings from: *The Second International Conference on the Teaching of Mathematics at the Undergraduate Level*. Hoboken, NJ: Wiley.
- Kaiser, G., Blomhøj, M., & Sriraman, B. (2006). Towards a didactical theory for mathematical modelling. *Zentralblatt für Didaktik der Mathematik, 38*, 82-85.
- Kaiser, G., Blum, W., Ferri, R. B., & Stillman, G. (2011). *Trends in teaching and learning of mathematical modeling*. New York: Springer.

- Kaya, S. (2007). *The influences of student views related to mathematics and self-regulated learning on achievement of algebra I students* (Unpublished doctoral dissertation). Ohio State University, Ohio.
- Kitsantas, A., & Dabbagh, N. (2010). *Learning to learn with Integrative Learning Technologies (ILT): A practical guide for academic success*. Greenwich, CT: Information Age Publishing.
- Kline, R. B. (1998). *Principles and practice of structural equation modeling* (1st ed.). New York, NY: Guilford Press.
- Kline, P. (2000). *Handbook of Psychological Testing* (2nd ed.). New York, NY: Routledge.
- Kline, R. B. (2005). *Principles and practice of structural equation modeling* (2nd ed.). New York, NY: Guilford Press.
- Kramarski, B. (2004). Making sense of graphs: Does metacognitive instruction make a difference on students' mathematical conceptions and alternative conceptions. *Learning and Instruction, 14*, 593-619.
- Kramarski, B., Mavarech, Z. R., & Arami, M. (2002). The effects of metacognitive instruction on solving mathematical tasks. *Educational Studies in Mathematics, 49*, 225-250.
- Larson, C., Harel, G., Oehrtman, M., Zandieh, M., Rasmussen, C., Speiser, R., & Walter, C. (2010). In R. Lesh, P. L. Galbraith, C. R. Haines, & A. Hurford (Eds.), *Modeling students' mathematical modeling competencies* (pp. 61-74). New York: Springer.
- Lehrer, R., & Schauble, L. (2003). Origins and evolution of model-based reasoning in mathematics and science. In R. Lesh & H. M. Doerr (Eds.), *Beyond constructivism: A models and modeling perspective on mathematics problem solving, learning, and teaching*. (pp. 59-70). Mahwah, NJ: Lawrence Erlbaum Associates.
- Lemke, M., Sen, A., Pahlke, E., Partelow, L., Miller, D., Williams, T., Kastberg, D., Jocelyn, L. (2004). International Outcomes of Learning in Mathematics Literacy and Problem Solving: PISA 2003 Results From the U.S. Perspective. (NCES 2005-003). Washington, DC: U.S. Department of Education, National Center for Education Statistics.
- Lesh, R. (2000). Beyond constructivism: Identifying mathematical abilities that are most needed for success beyond school in an age of information. *Mathematics Education Research Journal, 12*, 177-195.

- Lesh, R. (2003). How mathematizing reality is different from realizing mathematics. In S. J. Lamon, W. A. Parker, and S. K. Houston (Eds.), *Mathematical modeling: A way of life ICTMA11* (pp. 37-52). Chichester: Horwood Publishing.
- Lesh, R., & Doerr, H. M. (2003). *Beyond constructivism: Models and modeling perspectives on mathematics problem solving, learning, and teaching*. Mahwah, NJ: Lawrence Erlbaum Associates.
- Lesh, R., & Harrel, G. (2003). Problem solving, modeling, and local conceptual development. *Mathematical Thinking and Learning*, 5, 157-189.
- Lesh, R., Hoover, M., Hole, B., Kelly, A., & Post, T. (2000). Principles for developing thought-revealing activities for students and teachers. In A. Kelly & R. Lesh (Eds.), *Handbook of research design in mathematics and science education* (pp. 591-646). Mahwah, NJ: Lawrence Erlbaum.
- Lesh, R., & Lehrer, R. (2003). Models and modeling perspectives on the development of students and teachers. *Mathematical Thinking and Learning: An International Journal*, 5, 109-130.
- Lesh, R., Lester, F. K., & Hjalmarson, M. (2003). A models and modeling perspective on metacognitive functioning in everyday situations where problem solvers develop mathematical constructs. In R. Lesh and H. M. Doerr (Eds.), *Beyond constructivism: Models and modeling perspectives on mathematics problem solving, learning, and teaching* (pp. 383-404). Mahwah, NJ: Lawrence Erlbaum Associates.
- Lesh, R., & Yoon, C. (2004). What is distinctive in (our views about) models and modeling perspectives on mathematical problem solving, learning, and teaching? In H. Henn & W. Blum (Eds.), *ICMI study 14: Applications and modeling in mathematics education*. Pre-conference volume.
- Lesh, R., Yoon, C., & Zawojewski, J. (2007). John Dewey revisited – making mathematical practical versus making practice mathematical. In R. Lesh, E. Hamilton, & J. Kaput (Eds.), *Models and modeling as foundations for the future in mathematics education*. Mahwah, NJ: Lawrence Erlbaum Associates.
- Lesh, R., & Zawojewski, J. (2007) Problem solving and modeling. In F. K. Lester, Jr. (Ed.) *Second handbook of research on mathematics teaching and learning* (pp. 763 – 804). Greenwich, CT: IAP.
- Lesh, R., Zawojewski, J., & Carmona, G. (2003). What mathematical abilities are needed for success beyond school in a technology-based age of information? In R. Lesh and H. M. Doerr (Eds.), *Beyond constructivism: Models and modeling perspectives on mathematics problem solving, learning, and teaching* (pp. 205-222). Mahwah, NJ: Lawrence Erlbaum Associates.

- Maab, K., & Gurlitt, J. (2011). LEMA- Professional development of teachers in relation to mathematical modeling. In G. Kaiser, W. Blum, R. B. Ferri, & G. Stillman (Eds.), *Trends in teaching and learning of mathematical modeling* (pp. 629-640). New York: Springer.
- MacKinnon, D. P., Lockwood, C. M., & Williams, J. (2004). Confidence limits for the indirect effect: Distribution of the product and resampling methods. *Multivariate Behavioral Research, 39*, 99–128.
- Magiera, M.S., & Zawojewski, J. S. (2011). The social- and self-based contexts associated with students' awareness, evaluation and regulation of their thinking during small-group mathematical modeling. *Journal for Research in Mathematics Education, 42*, 486-520.
- Marsh, H. W., Balla, J. R., & McDonald, R. P. (1988). Goodness of fit indexes in confirmatory factor analysis: The effect of sample size. *Psychological Bulletin, 103*, 391-410.
- Mathieu, J. E., & Taylor, S. R. (2006). Clarifying conditions and decision points for mediational type inferences in organizational behavior. *Journal of Organizational Behavior, 27*, 1031-1056.
- McDonald, R.P., & Ho, M.H.R. (2002). Principles and practice in reporting statistical equation analyses. *Psychological Methods, 7*, 64-82.
- Mevarech, Z. R., & Kramarski, B. (1997). IMPROVE: A multidimensional method for teaching mathematics in heterogeneous classrooms. *American Educational Research Journal, 34*, 365-395.
- Miles, J., & Shevlin, M. (2007). A time and a place for incremental fit indices. *Personality and Individual Differences, 42*, 869-874.
- Mousoulides, N. (2007). *A modeling perspective in the teaching and learning of mathematical problem solving* (Unpublished doctoral dissertation). University of Cyprus, Cyprus.
- Mousoulides, N., Christou, C., & Sriraman, B. (2008). A modeling perspective on the teaching and learning of mathematical problem solving. *Mathematical Thinking and Learning, 10*, 293-304.
- Mousoulides, N., Pittalis, M., Christou, C., & Sriraman, B. (2010). Tracing students modeling processes in school. In R. Lesh, P. L. Galbraith, C. R. Haines, & A. Hurford (Eds.), *Modeling students' mathematical modeling competencies* (pp. 119-132). New York: Springer.
- Mullis, I.V.S., Martin, M.O., & Foy, P. (2008). *TIMSS 2007 international mathematics report: Findings from IEA's Trends in International Mathematics and Science Study at the fourth and eighth grades*. Chestnut Hill, MA: Boston College.

- Mundfrom, D. J., Shaw, D. G., & Ke, T. L. (2005). Minimum sample size recommendations for conducting factor analyses. *International Journal of Testing*, 5, 159-168.
- Muthén, L.K., & Muthén, B.O. (1998-2012). *Mplus User's Guide* (7th Edition). Los Angeles, CA: Author.
- National Research Council (2011). *Assessing 21st century skills: Summary of a workshop*. Washington, D.C.: The National Academic Press. Retrieved from <http://www.ncbi.nlm.nih.gov/books/NBK84218/pdf/TOC.pdf>
- Newell, A., & Simon, H. A. (1972). *Human problem solving*. Englewood Cliffs, NJ, Prentice-Hall.
- Nicolidau, M. & Philippou, G. (2004). Attitudes towards mathematics, self-efficacy and achievement in problem solving. *European Research in Mathematics Education III*, Thematic Group 2, 1-11.
- Organization for Economic Co-Operation and Development (2004). *Problem solving for tomorrow's world—First measures of cross curricular competencies from PISA 2003*. Retrieved from <http://www.oecd.org/dataoecd/25/12/34009000.pdf>.
- Ormrod, J. E. (2008). *Human learning* (5th ed.). Upper Saddle River, NJ: Prentice Hall.
- Pajares, F. (1996). Self-efficacy beliefs in academic settings. *Review of Educational research*, 66, 543-578.
- Pajares, F. (2008). Motivational role of self-efficacy beliefs in self-regulated learning. In D. H. Schunk & B. J. Zimmerman (Eds.), *Motivation and self-regulated learning* (pp.111-140). New York, NY: Lawrence Erlbaum Associates.
- Pajares, F., & Graham, L. (1999). Self-efficacy, motivation constructs, and mathematics performance of entering middle-school students. *Contemporary Educational Psychology*, 24, 124-139.
- Pajares, F., & Kranzler, J. (1995). Self-efficacy beliefs and general mental ability in mathematical problem solving. *Contemporary Educational Psychology*, 20, 426-443.
- Pajares, F., & Miller, D. (1994). Role of self-efficacy and self-concept beliefs in mathematical problem solving: A path analysis. *Journal of Educational Psychology*, 86, 193-203.
- Pajares, F., & Valiante, G. (2001). Gender differences in writing motivation and achievement of middle school students: A function of gender orientation? *Contemporary Educational Psychology*, 24, 366-381.

- Pajares, F., & Urdan, T. (Eds.) (2006). *Self-efficacy beliefs of adolescents*. Greenwich, CT: Information Age.
- Pape, S. J., & Smith, C. (2002). Self-regulating mathematical skills. *Theory Into Practice, 41*, 93-101.
- Pape, S. J., & Wang, C. (2003). Middle School Children's Strategic Behavior: Classification and Relation to Academic Achievement and Mathematical Problem Solving. *Instructional Science, 31*, 419-449.
- Pintrich, P. R. (1989). The dynamic interplay of student motivation and cognition in the college classroom. In C. Ames, & M. Maehr, *Advances in motivation and achievement: Motivation enhancing environments*, vol. 6. (pp. 117-160). Greenwich, CT: JAI Press.
- Pintrich, P.R. (1999). The role of motivation in promoting and sustaining self-regulated learning. *International Journal of Educational Research, 31*, 459-470.
- Pintrich, P. R., & De Groot, E. V. (1990). Motivational and self-regulated learning components of classroom academic performance. *Journal of Educational Psychology, 82*, 33-40.
- Pintrich, P., Roeser, R., & De Groot, E. (1994). Classroom and individual differences in early adolescents' motivation and self-regulated learning. *Journal of Early Adolescence, 14*, 139-161.
- Pintrich, P.R., Smith, D.A.F., Garcia, T., McKeachie, W.J. (1991). *Motivated Strategies for Learning Questionnaire*. Ann Arbor, MI: The University of Michigan -590.
- Pintrich, P., Smith, D., Garcia, T., & McKeachie, W. (1993). Reliability and predictive validity of the Motivated Strategies for Learning Questionnaire (MSLQ). *Educational and Psychological Measurement, 53*, 810-813.
- Pólya, G. (1957). *How to Solve it*. Princeton, NJ: Princeton University Press.
- Preacher, K. J., & Hayes, A. F. (2004). SPSS and SAS procedures for estimating indirect effects in simple mediation models. *Behavior Research Methods, Instruments, and Computers, 36*, 717-731.
- Preacher, K. J., Rucker, D. D., & Hayes, A. F. (2007). Addressing moderated mediation hypotheses: Theory, methods, and prescriptions. *Multivariate Behavioral Research, 42*, 185-227.
- Puteh, M., & Ibrahim, M. (2010) The usage of self-regulated learning strategies among four students in the mathematical problem-solving context: A case study. *Procedia Social and Behavioral Sciences, 8*, 446-452.

- Schunk, D. H. (1983a). Developing children's self-efficacy and skills: The roles of social comparative information and goal setting. *Contemporary Educational Psychology*, 8, 76-86.
- Schunk, D. H. (2000). Motivation for achievement: Past, present, and future. *Issues in Education*, 6, 161-166.
- Schunk, D. H., & Ertmer, P. A. (2000). Self-regulation and academic learning: self-efficacy enhancing interventions. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 631–649). San Diego: Academic Press.
- Schunk, D. H., & Mullen, C. A. (2012). Self-efficacy as an engaged learner. In S. L. Christenson, A. L. Reschly, & C. Wylie (Eds.), *Handbook of research on student engagement* (pp. 219-236). New York: Springer.
- Schunk, D. H., & Pajares, F. (2005). Self-efficacy and competence beliefs in academic functioning. In A. J. Elliot & C. Dweck (Eds.), *Handbook of competence and motivation* (pp. 85-104). New York: Guilford.
- Schunk, D. H., & Pajares, F. (2009). Self-efficacy theory. In K. R. Wentzel & A. Wigfield (Eds.), *Handbook of motivation at school* (pp. 35-53). New York: Routledge.
- Schunk, D. H., & Zimmerman, B. J. (1994). *Self-regulation of learning and performance: Issues and educational applications*. Hillsdale, NJ: Erlbaum.
- Schunk, D.H., & Zimmerman, B.J. (Eds.) (1998). *Self-regulated learning: From teaching to self-reflective practice*. New York: Guilford Press.
- Schunk, D. H., & Zimmerman, B. J. (2008). *Motivation and self-regulated learning: Theory, research, and applications*. Erlbaum Associates Publishers: Mahwah.
- Shrout, P. E., & Bolger, N. (2002). Mediation in experimental and non-experimental studies: New procedures and recommendations. *Psychological Methods*, 7, 422–445.
- Stein, B., Haynes, A., Redding, M., Cecil, M., & Ennis, T. (2007). Assessing critical thinking in STEM and beyond. In M. Iskander (Ed.), *Innovations in E-learning, instructional technology, assessment, and engineering education* (pp. 79-82). New York: Springer.
- Tinsley, H. E. A., & Weiss, D. J. (2000). Interrater reliability and agreement. In H. E. A. Tinsley & S. D. Brown (Eds.), *Handbook of applied multivariate statistics and mathematical modeling* (pp. 95–124). San Diego, CA: Academic.
- Verschaffel, L., De Corte, E., Lasure, S., Van Vaerenbergh, G., Bogaerts, H., & Ratinckx, E. (1999). Learning to solve mathematical application problems: A design experiment with fifth graders. *Mathematical Thinking and Learning*, 1, 195- 229.

- Verschaffel, L., van Dooren, W., Greer, B., & Mukhopadhyay, S. (2010). Reconceptualising word problems as exercises in mathematical modeling. *Journal of Mathematical Didactics*, 31, 9-29.
- Widaman, K. F. (2006). Missing data: What to do with or without them. *Monographs of the Society for Research in Child Development*, 71, 42–64.
- William, J., & MacKinnon, D. P. (2008). Resampling and distribution of the product methods for testing indirect effects in complex models. *Structural Equation Modeling*, 15, 23-51.
- Winnie, P. H., & Jamieson-Noel, D. (2002). Exploring students' calibration of self-reports about study tactics and achievement. *Contemporary Educational Psychology*, 27, 551-572.
- Wothke, W. (2000) Longitudinal and multigroup modeling with missing data. In T.D. Little, K.U. Schnabel, & J. Baumert (Eds.) *Modeling longitudinal and multilevel data: Practical issues, applied approaches, and specific examples*. Mahwah, NJ: Lawrence Erlbaum Associates.
- Zawojewski, J. (2010). Problem solving versus modeling. In R. Lesh, P. L. Galbraith, C. R. Haines, & A. Hurford (Eds.), *Modeling students' mathematical modeling competencies* (pp. 237-244). New York: Springer.
- Zimmerman, B. (1989). Self-regulated learning and academic achievement: An overview. *Educational Psychologist*, 25, 3-17.
- Zimmerman, B. J. (2000). Attaining self-regulation: A social cognitive perspective. In M. Boekaerts, P. Pintrich, & M. Ziedner (Eds.), *Handbook of self-regulation* (pp. 13-39). Orlando, FL: Academic Press.
- Zimmerman, B. J. (2002). Becoming a self-regulated learner: An overview. *Theory into Practice*, 41, 64 -72.
- Zimmerman, B. J. (2002a). Achieving self-regulation: The trial and triumph of adolescence. In F. Pajares & T. Urdan (Eds.) *Academic motivation of adolescents, Vol 2*. (pp. 1 – 27). Greenwich, CT: Information Age Publishing.
- Zimmerman, B. J. (2008). Investigating self-regulation and motivation: Historical background, methodological developments, and future prospects. *American Educational Research Journal*, 45, 166-183.
- Zimmerman, B. J., & Bandura, A. (1994). Impact of self-regulatory influences on writing course attainment. *American Educational Research Journal*, 31, 845-862.
- Zimmerman, B.J., Bandura, A., & Martinez-Pons, M. (1992). Self-motivation for academic attainment: The role of self-efficacy beliefs and personal goal setting, *American Educational Research Journal*, 29, 663-676.

- Zimmerman, B. J., & Campillo, M. (2003). Motivating self-regulated problem solvers. In J. E. Davidson & R. J. Sternberg (Eds.), *The psychology of problem solving* (pp. 233-262). New York: Cambridge University Press.
- Zimmerman, B.J., & Kitsantas, A. (2005). Homework practices and academic achievement: The mediating role of self-efficacy and perceived responsibility beliefs. *Contemporary Educational Psychology, 30*, 397–417.
- Zimmerman, B. J., & Martinez-Pons, M. (1986). Development of a structured interview for assessing students' use of self-regulated learning strategies. *American Educational Research Journal, 23*, 614-628.
- Zimmerman, B. J., & Martinez-Pons, M. (1988). Construct validation of a strategy model of student self-regulated learning. *Journal of Educational Psychology, 80*, 284-290.
- Zimmerman, B. J., & Martinez-Pons, M. (1990). Student differences in self-regulated learning: Relating grade, sex, and giftedness to self-efficacy and strategy use. *Journal of Educational Psychology, 82*, 51-59.
- Zhao, X., Lynch, J. G., & Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and truths about mediation analysis. *Journal of Consumer Research, 37*, 197-206.

BIOGRAPHICAL SKETCH

Anu Sharma graduated from Punjab University, Chandigarh (India) in the year 1997 with a Bachelor of Science in mathematics, physics, and chemistry. In 1998, she completed her Bachelor of Education from the same university. After graduation, she taught elementary level mathematics and science for 10 years at Kundan Vidya Mandir (KVM) School in Ludhiana, India. Anu also served as the coordinator for academics and co-curricular activities, supporting other faculty in curricular, instructional, and assessment planning as well as organizing and managing various co-curricular activities. While teaching at KVM School, she also earned a degree in Master of Mathematics from Himachal Pradesh University, Shimla, India in 2006. Shortly after coming to the United States in 2008, Anu enrolled at the University of Florida as a graduate student to begin her PhD in Curriculum and Instruction with emphasis in mathematics education. As part of her doctoral program, she also earned a cognate in Educational Psychology. She passed her qualifying exams in December 2010 and her dissertation proposal was approved in September 2011. She received her PhD from the University of Florida in the summer of 2013 with an aim to continue exploring the possibilities of integrating modeling activities and self-regulated learning within regular classrooms. After graduating, she joined the Centre for Educational Testing and Evaluation at the University of Kansas as a post-doctoral researcher.