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A PROCESS ANALYSIS OF ENGINEERING PROBLEM SOLVING AND ASSESSMENT OF PROBLEM SOLVING SKILLS

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A PROCESS ANALYSIS OF ENGINEERING PROBLEM SOLVING AND ASSESSMENT OF PROBLEM SOLVING SKILLS

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ABSTRACT

In the engineering profession, one of the most critical skills to possess is accurate and efficient problem solving. Thus, engineering educators should strive to help students develop skills needed to become competent problem solvers. In order to measure the development of skills, it is necessary to assess student performance, identify any deficiencies present in problem solving attempts, and identify trends in performance over time. Through iterative assessment using standard assessment metrics, researchers/instructors are able to track trends in problem solving performance across time, which can serve as a gauge of students' learning gains.

This research endeavor studies the problem solving process of first year engineering students in order to assess how person and process factors influence problem-solving success. This research makes a contribution to the literature in engineering education by 1) providing a coding scheme that can be used to analyze problem solving attempts in terms of the process rather than just outcomes, 2) providing an assessment tool which can be used to measure performance along the seven stage problem solving cycle, and 3) describing the effects of person and process factors on problem solving performance.

DEDICATION

I would like to dedicate this manuscript to all my family and friends who have supported me throughout my academic career. Special thanks go out to my parents Thomas and Jane Grigg who were constantly there to encourage me and to push me to finish. I could not have done it without your love and support.

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CHAPTER ONE

INTRODUCTION TO RESEARCH

In the engineering profession, one of the most critical skills to possess is accurate and efficient problem solving. In 2008, the National Academy of Engineering published a set of 14 grand challenges that are awaiting engineering solutions for the most pressing problems in society. Some of these challenges include making solar energy economical, providing energy from fusion, providing access to clean water, and advancing health informatics (Perry, et al., 2008). One thing all of these challenges have in common is that they require strong problem solvers to determine feasible solutions. While engineers once worked almost exclusively in their specialized field, companies are now riddled with challenges that require solutions that integrate knowledge from various domains and are under even tighter time constraints. Therefore, proficiency in problem solving is even more valuable as industry begins to look to engineers to tackle problems involving such constraints as technological change (Jablokow, 2007), market globalization, and resource sustainability (Rugarcia, Felder, Woods, & Stice, 2000).

Another grand challenge urges educators to develop ways of advancing personalized learning, which is described as when "instruction is tailored to a student's individual needs" (Perry, et al., 2008). In the area of problem solving, researchers and instructors can use process analysis to uncover deficiencies in problem solving skills and pinpoint instructional needs of the student. Information obtained from process analysis can potentially be used to improve student awareness of performance deficiencies or used in developing instructional interventions to help students develop problem solving skills.

Before students can effectively solve real world problems, they must first build an engineering knowledge base and develop process skills used in the application of knowledge such as problem solving and self-assessment (Woods, Felder, Rugarcia, & Stice, 2000). Students must also construct conceptual frameworks that they can use to solve real world problems which are often complex and have conflicting goals or undefined system constraints (Jonassen, Strobel, & Lee, 2006).

In the search for behaviors that promote problem solving proficiency, research has classified variations in performance between expert and novice problem solvers (Chi, Glaser, & Farr, 1988) presumably because expert problem solutions exhibit more successful application of problem solving skills. However, methods used by experts to solve problems are not necessarily transferable to novices due to cognitive requirements necessary to use these strategies. Cognitive overload may be a hindrance to achieving proficiency, including the inability to solve the problem without acquiring more information, lack of awareness of performance errors, and resistance to changing a selected method or representation (Wang & Chiew, 2010). Specifically, to encourage the development of problem solving skills, recommended techniques include: describing your thoughts while solving the problem, writing things down to reduce cognitive load, focusing on accuracy not speed, and monitoring one's progression throughout the problem solving process (Woods, et al., 2000).

Significance of the Study

Often instructors find that students, especially those in their first year of study, do not have the prerequisite knowledge needed or have strong enough analytical skills to demonstrate that they have learned new concepts. The instructor may feel the need to review prerequisite material to the entire class before continuing to new concepts. However, this is not an efficient use of time and can cause frustration in students who already mastered the material. A more effective method is to address individual students experiencing problems directly; providing specific and focused feedback. By analyzing the problem solving processes of students, instructors and researchers can uncover deficiencies in problem solving skills and pinpoint instructional needs of the student. From an instructional standpoint, this would enable personalized instruction for each student addressing individual problem solving needs, rather than addressing the class as a whole and subjecting students to instructional interventions that are irrelevant to them. From a research perspective, this would provide a method for assessing the effectiveness of different strategies used to solve problems or assessing the effectiveness of instructional interventions aimed at developing problem solving skills.

The specific aims of this research were to 1) provide a coding scheme that can be used to analyze problem solving attempts in terms of the process in addition to outcomes, 2) provide an assessment tool which can be used to measure performance of problem solving skills, and 3) describe the factors that influence problem solving performance.

OVERVIEW

The problem solving processes of a sample of students enrolled in a first year engineering course, “Engineering Disciplines and Skills” at Clemson University, were used for subsequent analyses. This study resulted in a better understanding of how students solved problems and an assessment method for evaluating problem solving proficiency. A thorough analysis of the literature has been conducted in order to identify potential factors that would influence students’ problem solving performances. Chapter 2 is a review of theoretical frameworks and research investigations that give insight to the problem solving process and performance outcomes.

Chapters 3-5 are methodological in nature. An introduction to the research methods including a description of available data sources is described in Chapter 3. In order to conduct the evaluation of problem solving attempts, a coding scheme was developed and a set of performance metrics were created. The development of the coding scheme is detailed in journal article form and is included in Chapter 4. A discussion of the development of the performance measures is included in Chapter 5.

Chapters 6-8 are set up as journal articles and describe the results of this research investigation. Chapters 6-7 take an in depth look at the variation between solutions in terms of the relation to solution accuracy (Chapter 6) and mental workload (Chapter 7). Chapter 8 turns the focus toward the student and looks for factors that contribute to variations in problem solving processes. Finally, Chapter 9 reports on a synthesis of the findings from Chapters 6-8 and offers an evidence-based assessment tool that can be used by instructors and researchers to assess student problem solving performances in similar contexts.

The four research questions under investigation included:

1) What aspects of problem solving attempts are more prevalent in successful solutions? (Chapter 6)
2) What are the relationships between mental workload and problem solving performance? (Chapter 7)
3) What are the relationships between academic preparation in mathematics and engineering and how students solve problems? (Chapter 8)
4) How can process-based analysis be used to enhance the assessment of problem solving attempts, especially in terms of problem solving skills? (Chapter 9)

CHAPTER TWO

LITERATURE REVIEW

This chapter introduces the theoretical framework of this research effort including various theories of information processing and problem solving. It also summarizes key findings of research on factors influencing problem solving performance and methods of performance measurement. Subsequent chapters also contain a review of literature related to the specific research question under investigation.

INFORMATION PROCESSING MODELS

Information processing theory was developed in order to model cognition (human thought) and describes how people take in information, process it, and generate an output. Wickens' Information Processing Model explains how stimuli are first perceived via the senses with help from cognitive resources, processed to make a decision and response selection, and then the response is executed. Throughout this process, people utilize attentional resources, working memory, and long term memory in the information processing cycle. Cognitive demands on memory and attention processes can overload the system and lead to errors in processing. Errors associated with overload of cognitive demand occur due to limitations of knowledge or skills currently held in long term memory and a low working memory capacity (Proctor & Van Zandt, 2008).

Baddeley and Hitch's model of working memory has three components: the visio-spatial sketch pad, the phonological loop, and the central executive. The visio-spatial sketch pad stores visual and spatial information while the phonological loop stores auditory information long enough to be utilized by the central executive function to integrate information from long term memory and encode the information (Baddley, 2003). Some functions of the central executive include monitoring and correcting errors, retrieving information from long term memory, and inhibiting irrelevant information (Esgate, Groome, & Baker, 2005). Cognitive overload happens frequently because people can only process a limited amount of information at a time (Miller, 1956). Cognitive (or mental) workload has similar effects on performance as arousal, with performance being highest under moderate workload conditions and deteriorating in response to underload or overload. Workload increases with the number of tasks to be performed, as required accuracy levels increase, as time demand increase, and based on cognitive capacities of the individual (Proctor & Van Zandt, 2008).

Cognitive Load Theory was developed by Sweller based on information processing theories through his research on problem solving tasks. He put forth three main forms of cognitive load attributable to the task: 1) intrinsic cognitive load – that characteristic of the material, 2) Extraneous load – that attributable to the activities required of the student, and 3) Germane load - that effort required to construct schemas. He suggests streamlining the design of instructional material to help learners quickly develop schemas and enhance knowledge acquisition and performance (Sweller, 1988).

Sternberg's Triarchic Theory of Human Intelligence builds on information processing theories to describe analytical intelligence, the form of intelligence utilized in problem solving. This theory breaks analytical intelligence into three components: metacomponents, performance components, and knowledge acquisition components. Metacomponents (i.e., metacognition) are higher-level central executive functions that consist of planning, monitoring, and evaluating the problem solving process. Performance components are the cognitive processes that complete operations in working memory such as making calculations, comparing data, or encoding information. Knowledge acquisition components are the processes used to gain or store new knowledge in long term memory (Sternberg, 1985).

According to Mayer, there are three main cognitive processes utilized in information processing during arithmetic type problem solving: selecting, organizing, and integrating information (Mayer, 2008). Mayer also describes three kinds of cognitive load associated with working memory processes: extraneous cognitive processing, essential cognitive processing, and generative cognitive processing. Extraneous cognitive processing is characterized by utilizing inappropriate approaches or using irrelevant information. Essential cognitive processing involves the difficulty of material compared to the knowledge base. Generative cognitive processing is affected by the motivation of the students' willingness to work to understand material. Mayer suggests that educators should work to minimize extraneous processing, manage essential processing, and foster generative processing (Mayer, 2008).

PROBLEM SOLVING THEORIES

Problem solving is a complex activity that requires synthesis of several different processing activities to transition from an initial problem state to the final goal state. Due to the complexity of the problem solving process, researchers have attempted to break down the problem solving process into elements (or parts) to enable analysis that is more precise. Additionally, prior research has focused on assessment within specific content domains to reduce the complexity of analysis and ensure the applicability of predictions made about the learners' performance (Peterson, Fennema, Carpenter, & Loef, 1989); however, this has led to variability in the assessment of problem solving and results that are difficult to generalize across contexts. There remains a need for better standardization of terminology, better measures to assess problem solving performance, and improved research methods (Lester Jr., 1994).

Several theoretical frameworks have been developed to describe problem solving in contexts as diverse as explaining insights in creativity (Wallas, 1926), heuristics in mathematics (Polya, 1957), and strategies in chess (Simon & Simon, 1978). Wallas' work serves as a model for insight problem solving, described in four stages:
1) preparation 2) incubation, 3) inspiration, and 4) verification (Wallas, 1926). Many researchers view insight problems, those involving an "ah ha" moment of clarity, as different from traditional problems, while others argue that insight is a result of typical cognitive processes (Bowden, Jung-Beeman, Fleck, & Kounios, 2005).

The first widely accepted problem solving methodology is credited to George Polya. He describes the act of problem solving in four steps: 1) understanding the problem, 2) devising a plan, 3) carrying out the plan, and 4) looking back or reviewing (Polya, 1957). However, this model implies that problem solving is a linear process that can be memorized when in fact problem solving is an iterative process where the subject may transition back to previous steps (Wilson, Fernandez, & Hadaway, 1993).

In the 1980s and 1990s, the problem solving process was expanded into a seven stage cycle based on Sternberg's Triachic Theory of Human Intelligence (Sternberg, 1985). The stages are the higher-level tasks driving the problem solving process (metacomponents), though both higher and lower level functions are required to complete these stages. While this structure gives a more complete view of the stages of problem solving, in practice, there is much variability in how people approach the problem and to what level the stage is completed (Wilson, et al., 1993). Pretz, Naples & Sternberg also point out the iterative, non-linear nature of the cycle, indicating that the problem solver may return to any of these stages at any time as their conceptualization of the problem changes (Pretz, Naples, & Sternberg, 2003). The cycle consists of:

1) recognizing / identifying the problem,
2) define and represent the problem mentally,
3) develop a solution strategy,
4) organize knowledge about the problem,
5) allocate resources for solving the problem,

6) monitor progress toward the goals, and

7) evaluate the solution for accuracy.

Greeno and Riley looked at the flow of information within the problem solving process. The model of problem understanding and solution describes how the problem solver must transform information from the problem text into problem schemata and then an action schema before arriving at a solution. This model, illustrated in Figure 2.1, identifies three stages to problem understanding 1) comprehension of the problem, 2) mapping concepts to procedures, and 3) execution of procedures (Greeno & Riley, 1987).

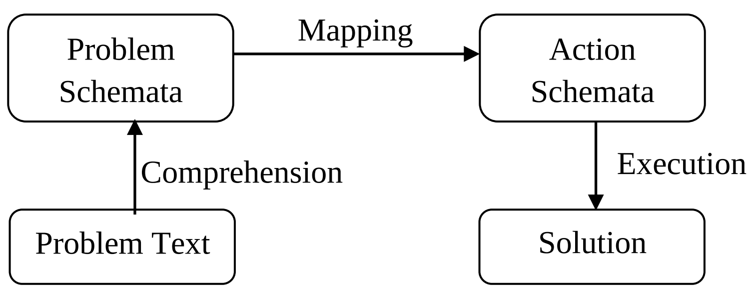


Figure 2.1: Model of problem understanding and solution

Redrawn from (Greeno & Riley, 1987)

Other theories broaden the model of problem solving to include factors beyond cognitive processing limitations, recognizing environmental/social factors and other person factors. Kirton's Cognitive Function Schema describes cognition as consisting of three main functions, cognitive resources (including knowledge, skills, and prior experiences), cognitive affect (needs, values, attitudes, and beliefs), and cognitive effect (potential level and preferred style) (Kirton, 2003). Jablokow described the general model of problem solving, based on Kirton's model, as a person conducting a process to create a product within a given environment (Figure 2.2). The environment provides the *opportunity* and the *motives* that may influence the problem solver. From there, the process is influenced by the problem solvers' *potential level* and *preferred style* in order to arrive at the product (Jablokow, 2007). Kirton adds that modifying behaviors also influence the outcome of the product. Modifying behaviors are those behaviors that are used in addition to or in spite of the *preferred style* of the problem solver (Kirton, 2003). Therefore, techniques that are taught can become present in the typical behaviors of the problem solver if there is strong enough motivation to perform those behaviors.

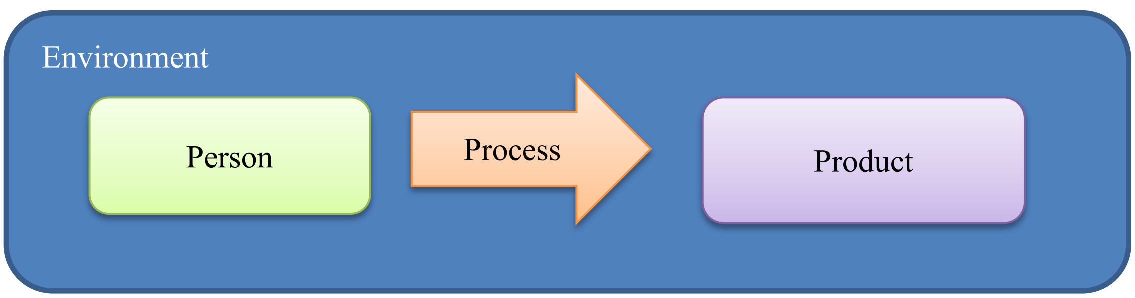


Figure 2.2: General Model of Problem Solving

Redrawn from (Jablokow, 2007)

FACTORS INFLUENCING PROBLEM SOLVING PERFORMANCE

A synthesis of research has shown that characteristics of the environment, such as teaching style and problem difficulty; the person, such as prior knowledge; and the process, such as cognitive and metacognitive tasks and strategies, influence problem solving performance.

Characteristics of the Environment

The learning environment can have a great impact on a student's ability to develop process skills, such as problem solving. Instructors can promote skills development by establishing a learning environment that provides practice applying the skill, encourages monitoring and reflection, grades the process rather than just the solution, utilizes standardized assessment and feedback, and teaches behaviors that have been shown to promote successful application of the skill (Woods, et al., 2000). Learning activities also need to be at an appropriate level that is challenging enough to promote learning, but achievable so students do not get frustrated or doubt their abilities. Funke described six features of a problem that contribute to its complexity (Funke, 1991):

1) Intransparency- lack of availability of information about the problem
2) Polytely- having multiple goals
3) Complexity of the situation- based on the number of variables and the type of relationship between the variables

4) Connectivity of variables- the impact on variables due to a change in one

5) Dynamic developments- worsening conditions lead to time pressures

6) Time-delayed effects- one must wait to see the impact of changes

Extensive work by Jonassen defines various problem types and gives insight into choosing appropriate problem types for the level of student and the outcomes being assessed. For example, well-structured problems such as story problems are appropriate for introducing students to new concepts and measuring arithmetic abilities, whereas ill-structured problems such as design problems are more appropriate for measuring a student's ability to weigh alternatives and make comparative judgments among alternative solutions (Jonassen & Hung, 2008). However, Pretz, Naples, & Sternberg point out that the U.S. educational system's overreliance on well-defined problems causes students to be underexposed to practice using planning metacognitive processes of recognizing, defining, and representing problems (Pretz, et al., 2003), which limits the students development of these skills.

Characteristics of the Problem Solver

In much of problem solving research, the effectiveness of strategies is described in terms of expert or novice performance. However, methods used by experts to solve problems are not necessarily transferable to novices due to cognitive requirements of using these strategies. For example, novices may have less knowledge on which to draw conclusions and may experience an overload of cognitive resources when using expert methods. Some of the major hindrances to achieving expert performance are the inability to solve the problem without acquiring more information, lack of awareness of performance errors, and resistance to changing a selected method or representation (Wang & Chiew, 2010).

Expertise level has been used to explain many performance differences between problem solvers. Novices commit more errors and have different approaches than experts (Chi, Feltovich, & Glaser, 1981). Also, experts may be up to four times faster at determining solutions than novices, even though experts also take time to pause between retrieving equations or chunks of information (Chi, et al., 1981) and spend more time than novices in the problem representation phase of the problem solving process (Pretz, et al., 2003). Chess research showed that experts had better pattern recognition due to larger knowledge bases developed through practice. Experts also organize their information differently than novices, using more effective chunking of information than novices (Larkin, Mcdermott, Simon, & Simon, 1980a), which is characteristic of higher performing working memory. Research suggests that people can improve performance of working memory by utilizing efficient processing techniques of selecting only relevant information and organizing the information in chunks along with other strategies such as writing down information to relieve cognitive demand (Matlin, 2001).

While it has been proposed that problem solving can be used to meet instructional goals such as learning facts, concepts, and procedures (Wilson, et al., 1993), research has shown that insufficient cognitive workload capacity may hinder learning throughout the problem solving task (Sweller, 1988). If a student's workload capacity is low, then (s)he may lack enough excess capacity to encode new knowledge because lower level tasks are not being performed efficiently. Low cognitive workload capacity is believed to be related to the Einstellung effect, where someone continues to use an inefficient yet effective approach, failing to realize there is a more efficient approach. Higher cognitive workload capacity is predictive of higher performance when overcoming impasses in problem solving attempts by enabling comparison of multiple attempts simultaneously held in working memory (Hambrick & Engle, 2003).

Characteristics of Problem Solving Processes

Variations in methods of expert and novice problem solvers were studied in the field of physics and two models were developed to illustrate the distinct process types. The Means-Ends novice model illustrates how novices progress through discrete stages of 1) selecting relevant information, 2) relating it to other information, and 3) using it. Means-end is a form of search strategy where given a current state and a goal state, an action is chosen that is believed will reduce the difference between the current state and the goal state. The Knowledge Development expert model illustrated how expert procedures were often "collapsed" into smaller steps that utilized larger chunks of information processing (Larkin, Mcdermott, Simon, & Simon, 1980b). Experts were also shown to have more efficient representations that include less irrelevant information and characterized key features needed for analysis. For example, when experts were asked to sort a series of physics problems, they grouped them based on the underlying theory needed to solve the problem, where novices grouped them based on surface features of the problems such as inclined planes (Chi, et al., 1988).

Another feature of problem solving performance is the level of metacognition used to manage the problem solving process. MacGregor, Ormerod, and Chronicle's Progress Monitoring theory offers two models of approaches used to monitor performance: 1) maximization heuristic, where problem solvers try to progress as far as possible on each attempt or 2) progress monitoring, where problem solvers assess progress toward the goal through incremental monitoring throughout the problem solving process and redirect the approach after realizing it will lead to an incorrect solution (Macgregor, Ormerod, & Chronicle, 2001). Problem solvers may fall to the maximization heuristics if they lack the capacity to perform the procedures of the progress monitoring model, which is more resource intensive.

Since cognitive resources are limited, people utilize strategies and heuristics to reduce cognitive load (Matlin, 2001). Table 2.1 shows a sample of strategies which have been observed in arithmetic problem solving, though this is hardly a comprehensive list (Crews, 2000; Nation & Siderman, 2004; Polya, 1957). While these strategies are useful in reducing cognitive load, they are not useful in all situations and may lead to an incorrect approach to solving the problem. Also people can become too reliant on strategies or use them inappropriately, leading to a decrement in performance (Matlin, 2001).

Table 2.1: Problem solving strategies compiled from

(Crews, 2000; Nation & Siderman, 2004; Polya, 1957)

Utilize a similar problem	Simplify the problem	Draw a picture / diagram
Pattern recognition	Use Logical Reasoning	Make a table
Work Backwards	Use Ratios	Guess and check

PERFORMANCE OUTCOME MEASURES

Outcomes can be measured in several ways, but typically, outcomes are simply assessed based on the accuracy of the final product. However, in human factors research, outcome measures can be divided into two classes: 1) performance measures which measure the persons' effect on the system, and 2) stress measures which measure the effect of the system on the person (Drury, 1990).

Performance Measures

The main metrics of task performance are the speed of task completion and the level of accuracy of the task outcomes (Drury, 1990). Optimal processes will both be quickly executed and have an accurate solution, but there is often a tradeoff between speed and accuracy, especially when learning a skill; therefore, giving an approximation of skill level. Accuracy is traditionally measured based on either overall conformance to requirements and a measure of the number of defects in the product. For problem solving solutions, this equates to final answer accuracy or a count of errors respectively.

Stress Measures

For cognitive tasks, the main stress measure is mental workload. There are several ways of assessing mental workload including primary task measures, secondary task measures, psychophysiological measures, and self-report assessments (Wilson & Corlett, 2005). In the classroom environment, self-report assessments lend themselves as the most practical measure based on their unobtrusive nature, ease of assessment, and quick data collection. The three most widely used subjective measures of mental workload are 1) the Modified Cooper-Harper scale, 2) NASA-Task Load Index (NASA-TLX), and 3) Subjective Workload Assessment Technique (SWAT). All three assessments are generic, can be applied to any domain, and are non- obtrusive to task performance when administered after the task.

The Modified Cooper-Harper Scale assesses difficulty level on a ten-item scale from very easy to impossible based on a classification of the demand level placed on the operator. Accurate assessment utilizing this scale requires the operator to carefully read each option and make fine distinctions between ratings of mental effort and ability to thwart errors. For example, the operator must distinguish between ratings such as "Maximum operator mental effort is required to avoid large or numerous errors" and "Intense operator mental effort is required to accomplish task, but frequent or numerous errors persist" (Wilson & Corlett, 2005). The Modified Cooper Harper scale cannot be used to diagnose sources of workload stress and the reliability is dependent on the operators acceptance and care to the task (Farmer & Brownson, 2003).

The NASA-TLX consists of six subscales, three measuring demand put on the participant by the task and three measuring stress added by the worker as a result of interacting with the task. The three measures of task demand include 1) mental demand, 2) physical demand, and 3) temporal demand. The remaining measures, 4) effort, 5) performance, and 6) frustration, describe the stress put on the person by the interaction of the person with the task (Warm, Matthews, & Finomore Jr., 2008). The NASA-TLX subscales are scored on a continuous scale from zero to twenty (Stanton, Salmon, Walker, Baber, & Jenkins, 2005). The NASA-TLX has been noted as highly reliable, extensively validated, has a high sensitivity, can be used to diagnose sources of workload and takes 1-2 minutes to complete (Farmer & Brownson, 2003).

The SWAT is a three item scale that rates time load, mental effort load, and psychological stress load on scales of 1-3. The scales do not easily translate to problem solving activities though because the assessment is geared toward tasks that take extensive time. For example, time load is measured on the three point scale: 1= Often have spare time, 2=Occasionally have spare time, and 3=Almost never have spare time. Additionally, SWAT has been criticized for being insensitive to low mental workloads (Stanton, et al., 2005) and has not been empirically validated (Farmer & Brownson, 2003).

CHAPTER THREE

RESEARCH METHODS

RESEARCH DESIGN

This study utilizes mixed methods, executed using a concurrent nested strategy for data collection. Concurrent nested strategies are characterized by data collection phases where both qualitative and quantitative data are collected and the data is mixed during analysis (Crewell, Plano Clark, Gutmann, & Loomis, 2003). In this study, measures of prior academic experiences were collected at the beginning of the semesters, followed by the collection of problem solutions, and, in Spring 2011, the collection of surveys of perceived mental workload at three points throughout the semester. All data was utilized concurrently in the evaluation of problem solving attempts and the impact of person and process factors on problem solving performance.

EXPERIMENTAL DESIGN

A repeated measures experimental design was used to evaluate relationships between predictive factors (participant and process) and outcome measures (accuracy, efficiency, and workload measures) across a range of engineering contexts. The sample group of students completed problem solving exercises three times.

Participants and Environment

First year engineering students enrolled in tablet sections of an engineering skill-building course at Clemson, "Engineering Disciplines and Skills," participated in this research. Students used tablet computers in the classroom on a regular basis (once per week, starting four weeks into the semester) to complete assignments using custom software in lieu of paper submissions of their regular class assignments.

Data was analyzed from two semesters: Fall 2009 and Spring 2011. Table 3.1 shows the sample of students who participated in the study. For Fall 2009, students were selected to participate from three different class sections. In Spring 2011, one entire section was studied and all submitted solutions were included in the analysis.

Table 3.1: Sampling of data from students enrolled in tablet sections of "Engineering Disciplines and Skills"

Semester	Total Enrolled Students (tablet sections)	Number of tablet sections	Number of participants	Sampling Rate
Fall 2009	150	3	27	18%
Spring 2011	40	1	36	90%

Engineering Problems

Four problems were used in this analysis, pertaining to the following topics: 1) efficiency, 2) circuits, and 3) pressure. Two different variations of the pressure problem were utilized across different semesters. The problems are included in Appendices A-C.

Problems needed to be structured enough for first year engineering students, but ill-defined enough to elicit students' problem-solving strategies upon analysis. Therefore, all problems 1) had a constrained context, including pre-defined elements (problem inputs), 2) allowed multiple predictable procedures or algorithms, and 3) had a single correct answer. All problems were story problems, in which students were presented with a narrative that embeds the values needed to obtain a final answer (Jonassen, 2010).

The first problem involved a multi-stage solar energy conversion system and required calculation of the efficiency of one stage given input and output values for the other stages. The second problem required students to solve for values of components in a given electrical circuit. This problem, developed by the project team, also contained a Rule-Using/Rule Induction portion (a problem having one correct solution but multiple rules governing the process (Jonassen, 2010)), where students were asked to determine an equivalent circuit based on a set of given constraints. The third problem involved total pressure calculations for a pressurized vessel and required students to solve for values within the system, and conversion between different unit systems.

DATA COLLECTION INSTRUMENTS

Four sources of data were collected from students: 1) solutions from three in-class activities (Fall 2009 and Spring 2011), 2) a beginning of semester survey on academic preparation (Fall 2009), and 3) the NASA-TLX for completed solutions (Spring 2011).

Problem Solutions Collected

Problem solving data were obtained via students' completed solutions using a program called *MuseInk*, developed at Clemson University (Bowman & Benson, 2010). This software was used in conjunction with tablet computers that were made available to all students during the class period. Students worked out problems in the *MuseInk* application, which digitally records ink strokes. *MuseInk* files (.mi) keep a running log of the entire problem solving process from beginning to end, including erasures, and can be replayed. Student work can be coded directly in the application at any point in time within the data file, thus allowing the researcher to associate codes to the problem solution directly in the file, even in portions of the solution that had been erased. Not all participants submitted solution files for every problem. Table 3.2 summarizes the number of solutions collected from students.

Table 3.2: Number of problem solutions collected for each problem

	Efficiency Problem	**Circuits Problem**	**Pressure Problem**
Fall 2009	24	22	22
Spring 2011	26	23	27
Total	**50**	**45**	**49**

Beginning of Semester Survey

At the beginning of each semester, a survey was sent out to all students enrolled in this course. In Fall 2009, prior knowledge measures were obtained from open ended responses to questions about a) previous mathematics courses and grades and b) participation in any pre-engineering activities. For Fall 2009 and Spring 2011, demographic information including gender and ethnicity was collected.

Mental Workload Survey

In Spring 2011, the NASA-TLX survey data was collected immediately following completion of selected written problem solutions for the entire class. The NASA-TLX (Hart, 2006) was chosen as the survey of choice because it is highly reliable, has been extensively validated, has a high sensitivity, can be used to diagnose sources of workload, and only takes 1-2 minutes to complete (Farmer & Brownson, 2003). Table 3.3 summarizes the number of surveys collected for each problem set. Only five of the six subscales were utilized in this analysis as the tasks were cognitive in nature, and physical demand should be irrelevant. In addition, the weighting protocol was eliminated as it has been shown to be unnecessary, prolongs the data collection process (Megaw, 2005), and would add unnecessary complexity to the data collection process.

Table 3.3: NASA-TLX data collected for each problem

	Efficiency Problem	**Circuits Problem**	**Pressure Problem**
Spring 2011	38	34	31

Data Analysis Methods

Data Transformation Methods

A task analysis approach was used to identify elements of the problem solving process including tasks, strategies, errors, and answer states observed in student work. The codes were generalized to tasks, strategies, and errors exhibited across various engineering problem sets so that a consistent analysis method can be used for different problems. Codes were assigned based on instances appearing within the work, where strategy codes were assigned based on interpretation of the overall process for each student's work. The data from this coding process were then transformed into measures believed to be indicators of problem solving skills level based on findings from the literature. Then, mixed models were used to evaluate the solutions in terms of process factors and performance measures while taking into account random factors attributed to the participant. Chapter 4 is an in-depth account of the development of this coding scheme. Chapter 5 is an extended description of the performance measures used in the evaluation.

Statistical Analyses

While the experimental design makes use of repeated measures, the primary interest is not the variation between problems and there is no attempt to assess gains between trials. For that reason, analyses will be conducted in two ways. First, samples were assessed as independent to identify and quantify any significant differences between groups. Second, linear mixed models were used to evaluate the predictive power of factors including effects of the problem on outcome measures of interest taking into account random factors attributed to the participant. This is used as an alternative to the repeated measures ANOVA as the rANOVA is highly vulnerable to effects of missing data and unequal time points between subjects (Gueorguieva R, 2004).

Data of various types are evaluated throughout subsequent chapters, thus requiring different statistical tests. The presence of a problem feature in a solution is of the binomial data type. However, performance measures are of a variety of data types including binomial and non-Gaussian types. Therefore, a variety of statistical tests were utilized. These tests are summarized in Table 3.4 and explained briefly below.

Table 3.4: Summary of statistical tests by data type

	Binomial Score (Two Possible Outcomes)	**Measurement (Non- Gaussian Population)**
Compare two unpaired groups	Chi-square goodness of fit test	Wilcoxon Rank Sum (Mann-Whitney test)
Quantify association between two variables	Odds ratios	Spearman correlation
Predict value from several measured or binomial variables	Multiple logistic regression	Multiple linear regression

Chi Squared Test: A Chi-square test is used to test how likely an observed distribution is due to chance. It is used to analyze categorical (binomial) data and evaluate whether there is a difference in population proportions (Gravetter & Wallnau, 2008). This analysis was used to assess whether the use of specific tasks, errors, and strategies differ between groups

Odds Ratios: To assess the likelihood of a an event occurring given another factor, odds ratios were calculated using a 2x2 contingency table depicting the number of cases in which an event occurs and does not occur for two mutually exclusive populations (Sheskin, 2004). Table 3.5 illustrates a sample contingency table, calculations 3.1-3.3 detail how to compute an odds ratio. This analysis was used to assess the magnitude by which the use of specific tasks, errors, and strategies differ between groups.

Table 3.5: Sample Contingency Table: odds ratios >1 indicate more likely events.

	Obtain a correct answer (1)	Do not obtain a correct answer (0)
Males (X)	a	b
Females (Y)	c	d

$$Odds(X) = \frac{p(X\ will\ occur)}{p(X\ will\ not\ occur)} = \frac{a/(a+b)}{b/(a+b)} \tag{3.1}$$

$$Odds(Y) = \frac{p(Y\ will\ occur)}{p(Y\ will\ not\ occur)} = \frac{c/(c+d)}{d/(c+d)} \tag{3.2}$$

$$Odds\ Ratio = \frac{Odds(X)}{Odds(Y)} = \frac{\left[\dfrac{a/(a+b)}{b/(a+b)}\right]}{\left[\dfrac{c/(c+d)}{d/(c+d)}\right]} \tag{3.3}$$

Wilcoxon Rank-Sum Test (Mann-Whitney U test): The Wilcoxon test is the non-parametric equivalent to the two sample t-test and is used to test whether there is a difference in the medians of two different groups was larger than due to chance. This tests were used when the group is a nominal variable and the comparison variable is of interval or ratio scale (Russo, 2003).

Pearson product-moment correlation coefficient/Spearman rho: Spearman's rho is the non-parametric equivalent of the Pearson product-moment correlation coefficient and used as a measure of linear association between two variables when at least one of the data types is ordinal in nature. In research on social science, associations around 0.10 are considered weak, 0.30 are considered moderate, 0.50 are considered strong, and 0.70 are considered very strong (Rosenthal, 2012).

Linear Mixed-Effects Models: Regression analysis is used to estimate the conditional expectation of the dependent variable given the independent variables. However, when samples are not independent, as is the case in repeated measures, mixed models are used to account for random factors such as the participant (Seltman, 2012).

CHAPTER FOUR:

DESIGN AND VALIDATION OF A CODING SCHEME FOR ANALYZING ENGINEERING PROBLEM SOLVING

This study introduces a coding scheme for analyzing problem solutions in terms of cognitive and metacognitive processes and problem solving deficiencies for first year engineering students. The coding scheme is presented with the development process, which may serve as a reference for other researchers analyzing complex tasks. A task analysis approach was used to assess students' problem solutions. A theoretical framework from mathematics research was utilized as a foundation to categorize the set of elements. The resulting coding scheme is comprised of 54 codes within the categories of knowledge access, knowledge generation, self-management, conceptual errors, mechanical errors, management errors, approach strategies, and solution accuracy. Inter-rater reliability (Cohen's Kappa) for two of the original coders was 0.769 for all coded elements and 0.942 when adjusted to assess agreement only on elements coded by both coders. The coding scheme was demonstrated to be reliable and valid for analyzing problems typical of topics in first year engineering courses. Task analyses allow the problem solving process to be evaluated in terms of time, process elements, errors committed, and self-corrected errors. Therefore, problem solving performance can be analyzed in terms of both accuracy and efficiency of processing, pinpointing areas meriting further study from a cognitive perspective, as well as areas of instructional need.

INTRODUCTION

In engineering professions, an important skill set to possess is accurate and efficient problem solving. While engineers once worked almost exclusively in their field of study, the practice of engineering is changing in the wake of a rapidly changing global economy. Companies are faced with new challenges that require integration of knowledge from various domains, and are often under tight time constraints to find solutions (National Academy of Engineering, 2004). Therefore, proficiency in problem solving is even more valuable as industry looks to engineers to tackle problems involving such constraints as technological change (Jablokow, 2007), market globalization, and resource sustainability (Rugarcia, et al., 2000). The National Academy of Engineers describes the necessary attributes of the engineer of 2020 as having ingenuity, problem solving capabilities, scientific insight, creativity, determination, leadership abilities, conscience, vision, and curiosity (2004).

In order to prepare for problem solving in the workplace, students must develop conceptual and procedural frameworks that they can use to solve real world problems that are often complex, have conflicting goals, and undefined system constraints (Jonassen, et al., 2006). However, students must first build an engineering knowledge base and develop process skills used in the application of knowledge such as problem solving and self-assessment (Woods, et al., 2000). Because of the importance of problem solving skills, educators should strive to help students obtain the knowledge resources and develop process skills required for problem solving success. In order to assess the development of problem-solving skills, it is necessary to be able to assess students' performances on a common set of criteria at various points in their studies.

The purpose of this research is to establish a standardized method for analyzing problem solutions in terms of characteristics that have been shown to indicate differences in skill level. This paper details the methodology used to develop a structured scheme for coding the solution processes of first year engineering students solving engineering problems independently, and presents the coding scheme as a valid instrument for assessing first year engineering students' problem solving skills using a mixed model methodology. For information on mixed model methodologies, see (Tashakkori & Teddlie, 1998).

LITERATURE REVIEW

Much research has been conducted on problem solving from a variety of perspectives. This review of relevant literature first describes the various models that have been proposed to explain the problem solving process, and then describes some of the factors that have been shown to impact problem solving success in the educational problem solving context.

Problem Solving Models

Several theoretical frameworks describe problem solving in contexts as diverse as explaining insights in creativity (Wallas, 1926), to heuristics in mathematics (Polya, 1957), and gaming strategies in chess (Simon & Simon, 1978). Wallas' model of problem solving serves as a model for insight problem solving, and describes creative problem solving in four stages: 1) preparation 2) incubation, 3) inspiration, and 4) verification (Wallas, 1926). The first widely-accepted problem solving methodology is credited to George Polya, who describes the act of problem solving in four steps: 1) understanding the problem, 2) devising a plan, 3) carrying out the plan, and 4) looking back or reviewing (Polya, 1957). However, like other heuristic models, the implication that problem solving is a linear process that can be memorized is flawed; problem solvers may iteratively transition back to previous steps (Wilson, et al., 1993).

A more recent model depicts problem solving as a seven stage cycle that emphasizes the iterative nature of the cycle (Pretz, et al., 2003). The stages include: 1) recognize / identify the problem, 2) define and represent the problem mentally, 3) develop a solution strategy, 4) organize knowledge about the problem, 5) allocate resources for solving the problem, 6) monitor progress toward the goals, and 7) evaluate the solution for accuracy. While this structure gives a more complete view of the stages of problem solving, in practice, there is much variability in how people approach the problem and how well each of the stages are completed, if at all (Wilson, et al., 1993).

The stages listed above are based on Sternberg's Triarchic Theory of Human

Intelligence, which breaks analytical intelligence, the form of intelligence utilized in problem solving, into three components: metacomponents, performance components, and knowledge acquisition components. Metacomponents (metacognition) are higher-level executive functions consisting of planning, monitoring, and evaluating the problem solving process. Performance components are the cognitive processes that perform operations such as making calculations, comparing data, or encoding information. Knowledge acquisition components are the processes used to gain or store new knowledge (Sternberg, 1985). The planning phase of the problem solving process consists of executive processes including problem recognition, definition, and representation (Pretz, et al., 2003). Pretz, Naples, & Sternberg point out that the educational system typically uses well-defined problems and therefore students may be underexposed to practice using planning metacognitive processes of recognizing, defining, and representing problems (Pretz, et al., 2003).

Other theories broaden the scope of factors influencing problem solving by recognizing environmental/social factors and other person factors beyond cognitive processing of knowledge. Kirton's Cognitive Function Schema describes cognition as consisting of three main functions, cognitive resources (including knowledge, skills, and prior experiences), cognitive affect (needs, values, attitudes, and beliefs), and cognitive effect (potential level and preferred style) (Kirton, 2003). The environment provides the *opportunity* and the *motives* that may influence the problem solver. From there, the process is influenced by the problem solvers' *potential level* and *preferred style* in order to arrive at the product (Jablokow, 2007). Kirton adds that modifying behaviors also influence the outcome of the product. Modifying behaviors are those behaviors that are used in addition to or in spite of the *preferred style* of the problem solver (Kirton, 2003). Therefore, techniques that are taught can become present in the typical behaviors of the problem solver if there is strong enough motivation to perform those behaviors.

Factors Influencing Problem Solving Success

Research in problem types and strategies has shown that characteristics of the *problem* such as the complexity or structure of the problem (Jonassen & Hung, 2008), the *person* such as prior experiences (Kirton, 2003) and reasoning skills(Jonassen & Hung, 2008), the *process* such as cognitive and metacognitive actions (Greeno & Riley, 1987; Sternberg, 1985) and strategies (Nickerson, 1994), and the *environment* such as the social context (Woods, et al., 2000) influence problem solving performance.

In the search for behaviors that promote proficiency in problem solving, much research has focused on classifying variations in performance between expert and novice problem solvers (Hutchinson, 1988) presumably because expert problem solutions exhibit more successful application of problem solving skills. Expertise level has been used to explain many performance differences between problem solvers. For example, research has shown that novices commit more errors and have different approaches than experts (Chi, et al., 1981). Experts have been shown to be up to four times faster at determining a solution than novices, even though experts also take time to pause between retrieving equations or chunks of information (Chi, et al., 1981) and spend more time than novices in the problem representation phase of the problem solving process (Pretz, et al., 2003). Experts also organize their information differently than novices, displaying larger chunking of information than novices (Larkin, et al., 1980a).

However, methods used by experts to solve problems are not necessarily transferable to novices due to cognitive requirements necessary to use these strategies. Cognitive overload may be a factor in some of the major hindrances to achieving proficiency including the inability to solve the problem without acquiring more information, lack of awareness of performance errors, and resistance to changing a selected method or representation (Wang & Chiew, 2010). Various strategies can be used in solving problems that alleviate some of the cognitive demand required by the problem, such as problem decomposition or subgoaling (Nickerson, 1994); however, people can become too reliant on strategies or use them inappropriately, leading to a decrement in performance (Matlin, 2001).

Less emphasis has been given to determining how to assess the development of problem solving skills. As Lester describes, there remains a need for better standardization of terminology used, better measures to assess problem solving performance, and improved research methods (Lester Jr., 1994).

METHODS

The objectives of this paper are twofold: 1) to describe the methodology used to develop a coding scheme such that it can serve as a guide to other researchers who seek to develop methods to analyze complex tasks, and 2) to present the coding scheme itself, which may be used by education researchers or instructors who wish to analyze problem solving in similar contexts. The coding scheme is used to analyze solutions from a variety of problems typical of an introductory engineering course. By analyzing multiple students' problem solving attempts, we can identify common variations in process types and evaluate the effect of person and process factors on problem solving performance. However, in order to enable comparison of processes across problem types, there must be a standardized means of analysis.

Educational Environment

Problem solutions were collected from first year engineering students in an introductory engineering course that is taught in a "studio" setting using active cooperative learning techniques. While students are regularly encouraged to work with their peers on in-class activities, students completed the problems in this study independently. Students in the course sections taught by a member of the research team were invited to participate in this study. Data was collected from 27 students; however not all students completed all three problems analyzed. In addition to problem solutions, other data collected from participants included demographics, and academic preparation before college enrollment (math and science courses taken, grades in those courses, and pre-college engineering activities or courses).

Engineering Problem Types

For this analysis, problems were chosen based on characteristics that would ensure moderate problem difficulty for students in a first year engineering classroom, who are building their engineering knowledge base and process skills. The chosen problems struck a balance of being well-structured enough to limit the cognitive load on the students, but remain challenging and provide multiple perspectives to solving the problem in accordance with the guidelines for problem-based learning (Jonassen & Hung, 2008). All problems had 1) a constrained context, including pre-defined elements (problem inputs), 2) allowed multiple predictable procedures or algorithms, and 3) had a single correct answer (Jonassen, 2004). Three problems were selected that reflected a variety of types of well-structured problems. Two originated from the course textbook (Stephan, Sill, Park, Bowman, & Ohland, 2011) and one was developed by the project team. All three problems were story problems, in which the student is presented with a narrative that embeds the values needed to obtain a final answer (Jonassen, 2010). The first problem involved a multi-stage solar energy conversion system and required calculation of the efficiency of one stage given input and output values for the other stages (Appendix A). The second problem required students to solve for values of components in a given electrical circuit (Appendix B). This problem, developed by the project team, also contained a Rule-Using/Rule Induction portion (a problem having one correct solution but multiple rules governing the process (Jonassen, 2010)), where students were asked to determine an equivalent circuit based on a set of given constraints. The third problem involved total pressure calculations and required students to solve for values within the system, and conversion between different unit systems (Appendix C).

Tablet PC Technology and Data Collection Software

In order to capture problem-solving processes for analysis, students wrote their solution attempts on a Tablet PC using a custom-designed software called *MuseInk* (Bowman & Benson, 2010; Grigg & Benson, 2011). The software allows students to work problems on a Tablet PC, and stores the digital Ink in such a way that it can be played back, annotated, and exported to a database where the data can be queried for analysis. Students work through problems much as they would with pen and paper, with the added benefit of having electronic access to their work, while researchers are provided with a comprehensive expression of the problem solving attempt from beginning to end including work that was erased in the process.

Analysis Methods

While several researchers have developed independent coding schemes to aid in the analysis of problem solving, most researchers have analyzed written work in conjunction with a think-aloud (Artzt & Armour-Thomas, 1992; Litzinger, et al., 2010; Weston, et al., 2001; Wong, Lawson, & Keeves, 2002). These coding schemes are tailored to analyze the students' verbal expressions of their work and not the elements explicitly contained in the artifact itself, i.e. the students' actual problem solution by which they communicate their problem solving competencies in the classroom. Coding schemes for assessing students' think-alouds are not readily applicable to the assessment of the written problem solutions. Yet, written data is rich in many ways, and analyzing tasks explicitly enacted under authentic problem solving conditions can reveal strategies or errors that occur organically and that may impact problem solving success.

A task analysis approach was utilized in order to develop a taxonomy of component and subcomponent tasks involved in problem solving solutions, along with a taxonomy of errors and strategies used by first year engineering students. Task analysis methods originate with the work of Gilbreth (Gilbreth, 1914) and Taylor (Taylor, 1911), whose work-study approaches were traditionally used to evaluate and improve the efficiency of workers (Stammers & Shepherd, 1990). The definition of task analysis has been broadened to include the qualitative assessment of humans interacting with a system or process in order to understand how to better match the demands of the task to the capabilities of the human (Wickens, Gordon, & Liu, 1998). The subcomponent tasks obtained from task analyses, referred to as elements, often serve as inputs for other forms of data analysis including error analysis and process charting techniques (Stanton, et al., 2005). Research in mathematics education describes the importance of error analysis as providing the opportunity to diagnose learning difficulties and develop criteria for differentiating education, so that instructors can tailor education to individual students in order to improve their performance and understanding (Radatz, 1980). While there is no consensus on what constitutes an element, typically they are defined as discrete, measureable, and repeatable units of activity, and it is at the researcher's discretion to assign elements that are appropriately sized for the intended analysis (Stammers & Shepherd, 1990).

CODING SCHEME DEVELOPMENT

The remainder of this paper describes the method used to develop a taxonomy of codes that will be used to analyze engineering problem solutions and validate the coding scheme against current literature.

1. Form an Interdisciplinary Team of Coders to Scrutinize the Coding Scheme

In order to ensure high quality codes, an interdisciplinary team was formed to assess problem solving solutions so that the coding scheme could undergo a high level of scrutiny from several different perspectives. The interdisciplinary team was made up of two faculty members, an instructor, and a graduate student. One faculty member instructs in engineering education as well as in a first year engineering program, with a background in bioengineering. The other faculty member is an instructor in secondary science education with a background in cognitive science. One team member was an instructor in a first year engineering program with a background in computer engineering. The graduate student was a lab instructor in industrial engineering with a background in human factors engineering. The variety of disciplines represented in the group allowed the team to refine codes to the language of the engineer that was generic enough to be applicable in a range of engineering topics.

2. Determine Requirements of the Coding Scheme

The long-term goal of our research is to examine the impact of prior academic experiences and process variations (such as cognitive skills, metacognitive skills, and strategies) on problem solving performance for engineering students. The coding scheme had to enable analysis of problem solutions in accordance with our variables of interest. Therefore, it had to distinguish between students drawing information from their prior knowledge, and students drawing information from the problem text. It also needed to distinguish between manipulating information for the purposes of solving the problem (cognitive tasks) and for the purposes of self-correcting (metacognitive tasks).

We also wanted to ensure that problem solving performance could be evaluated utilizing the information obtained using the coding scheme. Jonassen suggests a six item rubric of criteria to evaluate performance of story problems: 1) accuracy of problem classification, 2) identification of initial conditions, 3) accuracy of equations, 4) accuracy of answer estimate, 5) unit consistency, and 6) accuracy of answer (Jonassen, 2004).

However, these criteria only assess the accuracy of information gathered from the problem text and other resources, and solution accuracy. Our study looks at how well (if at all) students identify and correct errors (inconsistent units, incorrect equations, incorrect initial conditions, etc.) in addition to the accuracy of the solution.

3. Develop an Initial Coding Scheme

Once the requirements for the coding scheme were established, an appropriate structure for the coding scheme was identified. While there are several different approaches to creating a coding scheme, we utilized an a priori framework as a starting point and modified codes to fit our task and population. Researchers may wish to utilize a coding scheme as is or develop a new one from scratch using grounded theory (Hutchinson 1988). The choice depends on the availability of preexisting coding schemes to meet the research objectives.

We identified four major components necessary for our coding scheme: 1) process elements, 2) errors, 3) approach strategies, and 4) solution accuracy. The majority of the problem solving solution is coded through identifying process elements and errors if they are present. Approach strategy and final answer accuracy are classifications of the solution as a whole, and will only be coded at the end of the solution (or at the end of each part for multi-part problems).

Development of Process Elements Codes

Process elements are the backbone of the coding scheme and describe what the student is doing as depicted in the problem solution. For codes related to process elements, the basic structure set forth in the coding scheme by Wong, Lawson, and Keeves was used as an a priori framework. The framework was originally used to code student's videotaped activity while studying mathematical materials during a concurrent think-aloud to assess processing differences in students based on self-explanation training versus a control group that did not receive self-explanation training (Wong, et al., 2002). Similar to Sternberg's theoretical framework (Sternberg, 1985), this coding scheme separated elements into categories of knowledge access, knowledge generation, and self-management.

- Knowledge Access (KA) codes describe instances of the student retrieving knowledge not explicitly stated in the problem statement.
- Knowledge Generation (KG) codes describe instances of transforming bits of information to form new connections or relationships.
- Self-management (SM) codes describe tasks related to assessing the current state of problem solving activity.

The Wong et al. coding scheme provided the structure needed to distinguish between instances of retrieval of information from cognitive resources (Knowledge Access), cognitive elements (Knowledge Generation), and metacognitive elements (Self-Management). We segmented the Self-Management category according to elements of planning, monitoring, evaluating, and revising the solution in accordance to Hartman's definition of the executive management aspects of metacognition (Hartman, 2001).

Development of Error Codes

Error codes indicate instances where a problem first occurs; errors always occur in conjunction with a process element. For codes relating to errors, we utilized a structure derived from error detection literature in accounting, where it is common to classify errors as conceptual and mechanical errors (Owhoso, Messier, & Lynch Jr., 2002; Ramsay, 1994).We added a category for management errors to capture errors in metacognitive processes.

- Conceptual errors describe instances of misunderstanding of the problem and/or underlying fundamental concepts
- Mechanical errors describe instances of operation errors like miscalculations
- Management errors describe instances of mismanaging information including identify given information, transcribing values, or erasing correct work.

With this error coding structure, an improper equation selection or a flawed version of the correct equation would be classified as a conceptual error, but misusing a proper equation such as incorrectly manipulating an equation would be classified as a mechanical error. In this way, errors related to students' understanding of engineering concepts and their computational skills can be identified separately. This allows researchers to pinpoint hindrances to learning. For example, the case in which a student does not use the efficiency equation properly because s/he did not understand the concept of efficiency is a much different case than if the student erred in using the equation because s/he has difficulty manipulating equations due to weak algebra skills or inattention to details.

Development of Strategy Codes

Strategy codes are one time use codes that describe the overall approach taken to solve the problem. For strategy codes, we utilized a subset of strategies that appeared most applicable to story problems from the compilation described in "Thinking and Problem Solving" (Nickerson, 1994). The subset was refined from the broader list of strategies identified by Nickerson over the course of reviewing multiple problems completed by different students with different academic backgrounds.

Development of Solution Accuracy Codes

Solution accuracy codes are one time use codes that describe the accuracy of the final answer. While standard answer states of "correct" and "incorrect" could be used to describe the accuracy of the problem solution, two additional codes were included to further describe solutions: "Correct but Missing/Incorrect units", and "Gave up". These two codes are subsets of the Correct and Incorrect solutions respectively. Solutions coded as "Correct but Missing/Incorrect Units" are solutions in which the numerical value of the solution is correct, but the units are missing or the answer is given in a unit other than what was required, such as 120 seconds when the correct answer should have been reported in minutes. The code “Gave up” indicates that no final answer was obtained.

4. Establish a Coding Protocol

It is important to establish a protocol for how and where to assign codes to ensure consistency between coders. For the purposes of our research, the task of solving an engineering problem was broken down into discrete elements based on apparent changes in action such as transitions between identifying information from the problem statement, identifying information from their resources, manipulating information, and revising work. One unique function of the tablet-based software developed for this project, *MuseInk*, is that codes inserted in the work show up on the solution space, attached to a stroke within the solution like a map tack. This enables the code to be mapped to a specific point in the problem solving process. However, in order to use this feature most efficiently, it is important to code precisely at the point in time where the stroke is in order to avoid confusion when interpreting the data. To make best use of this functionality, it was established that all codes should be assigned at the end of an element for consistency. This also established a method for determining time between completions of activities. Additionally, it was determined that every erasure except correcting penmanship should be coded. Figure 4.1 depicts a snapshot of a code that is placed on a process element.

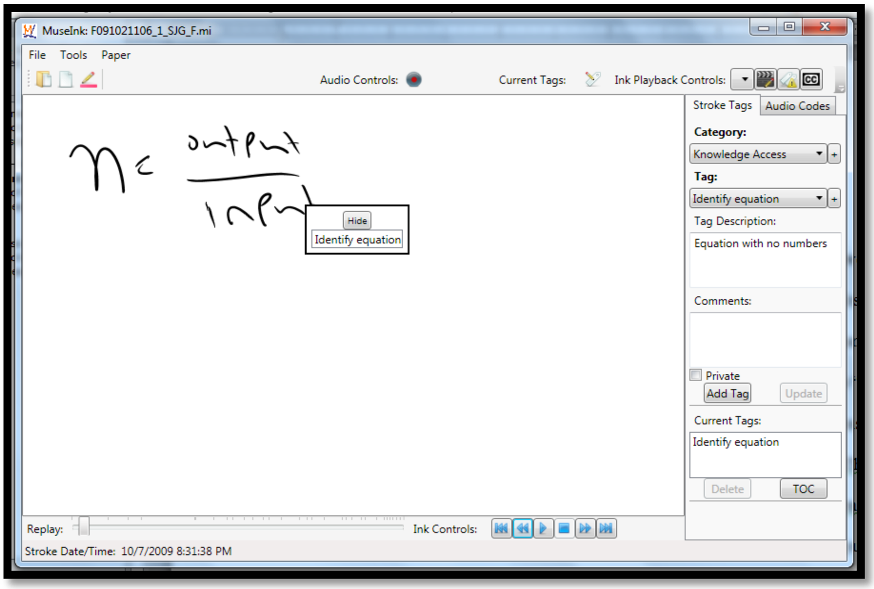


Figure 4.1: Image of a coded process element in *MuseInk*.

Here the student wrote the equation for efficiency, which was coded as

"Identify equation," within the Knowledge Access category.

The formal coding protocol is as follows. During the coding of problem solutions completed on a tablet computer with digital Ink, the coder first opens the *MuseInk* file and loads the "Tagging Universe". The Tagging Universe consists of an Excel workbook that holds the coding scheme organized by category names on different worksheets, with short descriptions of each code. Then coders enter "Replay Mode" in *MuseInk* and progress through the problem solution from beginning to end. Codes are assigned to the final stroke of each element so that it may be viewed with the assigned code when the problem is reviewed. Since a task analysis approach is utilized to assess the problem solving solution in terms of process, a new code is assigned for each transition in process (Konz & Johnson, 2004). Therefore, each segment of work is coded with one process element code and error codes are only assigned in association with a process element code. No error codes were assigned without an associated process element code.

5. Pilot test the Coding Process

Problem solutions for three students were selected at random (n = 24) from the solar efficiency problem for initial coding. One member of the research team initially reviewed the three solutions and began classifying processing elements present in the work within the KA, KG, and SM categories. Once an initial classification of problem solving processing elements was developed, the interdisciplinary team of researchers met to discuss the grouping of codes and ensure that 1) the codes were appropriate descriptions of the elements, 2) they were general enough to be applied to other problems, and 3) they were categorized appropriately according to the theoretical framework. In this collaborative session, the description of process elements was displayed in a spreadsheet on an overhead projector while the group verified the correct classification of each code one by one in accordance with the theoretical framework (Wong, et al., 2002), making changes as deemed appropriate. Ideas and concerns over potential changes to the codes were documented by writing notes directly on the spreadsheet using a tablet computer. A code book was established to define codes, describe how each code was to be used, provide contrasts with related codes that could be misinterpreted, and give examples. Coders can refer to the code book to ensure that developed procedures are followed consistently. Once a consensus was formed on codes, three members of the interdisciplinary team (those with engineering backgrounds) coded the three selected solutions. For the first round of coding, coders assigned codes independently and then reconvened to determine coding agreement.

6. Assess Reliability of the Coding Protocol

In order to evaluate the validity of the coding protocol and inter-rater reliability for the three coders, coded solutions were assessed on three criteria: 1) code agreement (i.e., Did all coders associate this particular code with the element?), 2) code frequency (i.e., Did all coders code the same number of elements?) and 3) code timing (i.e., Were elements coded by coders consistently at the same point within a solution, namely within five ink strokes of one another?).

Inter-rater reliability was calculated based on overall agreement rates for all coded elements as shown in calculation (1) and adjusted overall agreement rate for only elements coded by all coders as shown in calculation (2) (Gwet, 2010).

Overall Agreement Rate = # ratings in agreement / total # of ratings (1)

Adjusted Overall Agreement Rate =

ratings in agreement / (total # of ratings - # of ratings with missing data) (2)

"Agreement" was defined as an instance where a code was identified by all coders. "Missing data" was defined as an element that one coder applied a code to but another did not, which may be considered an important omission. In this study, inter-rater agreement was calculated both ways. Overall agreement (inclusion of missing data) answers the question, "To what degree do coders identify elements the same way?" This approach examines the degree to which coders can both identify elements and code elements accurately, and that the codes are sufficient for describing student problem solving. Adjusted overall agreement (dropping missing codes from the analysis) answers the questions, "To what degree are the codes sufficient for describing student problem solving? Given a set of identified elements, do two coders code elements similarly?" These questions examine the degree to which the codes sufficiently describe student work (validity of the coding system), and are reliably applied. While dropping missing data from the analysis reveals if coders are applying the same codes, such analysis does not account for the case in which actually identifying elements is an important part of the coding process. Therefore, missing data may be dropped from analysis to examine the codes and their application, but missing data should be retained for understanding the whole coding process that coders use in analyzing student work. An instance where coders fail to identify an element and apply a code signals a need for better coder training, or collapsing of codes so they are less specific and can be more broadly applied. In contrast, an instance of disagreement about what a code means might indicate that additional clarity around the meaning and interpretation of the codes is required.

Initial inter-rater reliability was calculated by examining only overall agreement (including missing data), to assess the whole coding process. Results showed an overall agreement rate of 55%, with individual agreement rates of 77%, 55%, and 42% for the three solutions. Reviewing the instances of disagreements was instrumental in identifying inconsistencies in applying codes and revealing missing problem solving features that were not captured in the initial coding scheme.

7. Iteratively Refine the Coding Scheme and Protocol

Two more iterations of revisions were conducted before reaching a satisfactory level of inter-rater reliability. For the second round of coding, three new students' solutions were coded and overall agreement calculated. Using the scoring classifications described in (Gwet, 2010), initial inter-rater reliability for the second round was "Moderate" with overall agreement lower than the initial round of coding (for the three solutions, inter-rater agreement was 73%, 40%, and 25%, for an overall agreement rate of 41%). This round of coding revealed that, with the addition of new codes and reconfiguring code categories, there was confusion with the use of specific codes as well as the frequency of assigning codes. The coding protocol was clarified and documented in the codebook. In order to improve the inter-rater reliability of coders, a round-robin review cycle was implemented for the next round of coding, in which each coded problem was reviewed by a second coder in order to perform an internal check of adherence to proper coding procedures.

During the next iteration, each rater coded three new students' solutions, and then reviewed coded data from one of the other two raters. In the case of discrepancies between raters (code reviewers identified codes that should be added or deleted), comments were added identifying the reviewer and the suggested action. Then the original rater reviewed the suggested changes and accepted or rejected them. The process whereby each submission was coded by each rater, then reviewed by another rater provided an intense learning session for the raters, which helped establish the final coding protocol.

The third round of coding showed greatly improved overall agreement rates. Using the scoring classifications described by Gwet (Gwet, 2010), the overall agreement rate was "almost perfect" for this round of coding. Across the three solutions, agreement rates were 100%, 96%, and 85%, for an overall agreement rate of 92%. Once this acceptable level of inter-rater reliability was reached, the rest of the students' solutions for the first problem were coded, with each rater coding eight and reviewing eight others coded by another rater. Twenty-four solutions were coded for the first problem including recoding solutions used in prior iterations of the coding scheme. Following the coding of the entire sample of the first problem (n = 24), the team reconvened to discuss any concerns with the coding scheme and coding protocol before moving on to code solutions for the two other problems.

8. Establish Generalizability of Coding Scheme

Coding progressed to include two additional problems with different context and features (the electrical circuit and total pressure problems). This iteration of coding was important to ensure that the coding scheme was robust enough to be used for a variety of problems within engineering contexts. For this iteration, solutions from one student were coded for three separate problems.

At this point in the development of the coding scheme, it was important to examine both the coding process as a whole and the reliability of the codes themselves. Thus, both overall agreement and adjusted overall agreement (removing instances of missing data) were calculated along with Cohen's Kappa coefficients for both measures of agreement. Two of the three original coders conducted this round of coding. The overall agreement rate was "substantial" (0.769) and adjusted overall agreement rate was "almost perfect" (0.942) (Gwet, 2010). A summary of results is shown in Table 4.1.

Table 4.1: Inter-rater reliability for two original raters calculated as overall agreement and adjusted overall agreement with Cohen's Kappa coefficients.

	Retain missing codes		Drop missing codes	
Problem	**Overall Agreement**	**Kappa**	**Adjusted Overall Agreement**	**Kappa**
1	87.5%	0.862	98.0%	0.977
2	73.91%	0.723	89.47%	0.887
3	73.68%	0.721	96.55%	0.963
Average	78.36%	0.769	94.67%	0.942

9. Assess Repeatability of Coding Scheme With New Rater

After a comprehensive coding scheme was developed, another member was brought into the team to serve as an additional check that other researchers beside those who developed the coding scheme can properly utilize the coding scheme. The new team member was a post-doctoral researcher with a background in computer science education. The new coder was trained in how to use the coding scheme by coding three solutions openly with another coder, discussing questions encountered, and subsequently updating the codebook. Once the new rater felt confident to progress, two of the initial raters along with the new rater assessed one problem from each of the three problem sets collected (the solar efficiency, electrical circuit, and total pressure problems) from one student.

Inter-rater agreement showed that agreement was acceptable. Again, both overall agreement and adjusted overall agreement (removing instances of missing data) were calculated along with Cohen's Kappa coefficients for both measures of agreement. As shown in Table 4.2, inter-rater reliability decreased with the addition of the new coder, but remained "substantial" for problems 1 and 2 and "almost perfect" when adjusted to remove data points with missing ratings. In problem 3, there was a fairly sizeable portion that was not coded because the student was iterating through the same element repeatedly and these iterations were not captured by the new coder, resulting in only "fair" agreement. For the efficiency problem from which the coding scheme was initially developed, the agreement rates were 70% (98% adjusted). The agreement rate was 62%

(94% adjusted) for the circuit problem, and 38% (94%) for the pressure problem, leading to an overall agreement rate of 57% (95% adjusted). Overall, Cohen's Kappa coefficients were 0.614 (0.948 adjusted) for a "substantial" level of inter rater reliability and "near perfect" level on adjusted scores. Overall, inter-rater reliability measures were encouraging and showed that the coding scheme is robust and detailed enough to achieve high reliability between raters. By the end of scheme development and training, coders were consistently assigning the same codes, though there remained some confusion for the new coder on when to assign a code (i.e. to code each instance of a task, even when the tasks were iteratively written and erased)

Table 4.2: Inter-rater reliability for two original coders + new coder calculated as overall agreement and adjusted overall agreement

	Retain missing codes		**Drop missing codes**	
Problem	**Overall Agreement**	**Kappa**	**Adjusted Overall Agreement**	**Kappa**
1	70%	0.718	98%	0.974
2	62%	0.654	94%	0.937
3	38%	0.470	94%	0.932
Average	57%	0.614	95%	0.948

10. Establish Validity of Coding Scheme

Validity is the extent to which evidence supports the analysis as a measure of the construct. One way of showing validity is through convergent validity, showing that the new assessment relates to other constructs it is supposed to relate to (Gatignon, 2009). We compared data from the analysis of the first problem (the solar efficiency problem) to ensure that the results obtained are in line with those obtained by others when examining problem solving with respect to expertise (Chi, et al., 1981). Tables 4.3 and 4.4 summarize the data used to make this comparison.

Solutions were divided into four groups based on their approach strategy (as a proxy of expertise level as evidenced in this particular solution). By stepping through the problem solving process, one can get a sense for the level of expertise of the problem solver through the strategies used based on how efficiently the problem solver moves toward the goal or synthesizes information. In order from lowest to highest level of elegance, the common strategies identified in this analysis included:

1) Plug and chug which involves inserting given values into an equation and producing an answer without necessarily understanding the problem (Wankat, 1999).
2) Guess and Check which is a slightly more sophisticated approach where the problem solver checks that the values inserted into an equation yields the correct units or checks for reasonableness of the solution (Wankat, 1999).
3) Problem Decomposition (segmentation) which involves breaking down a complex problem to ease analysis (Nickerson, 1994).
4) Clustering (chunking) which involves grouping like information into larger units (Chi, et al., 1981)

Table 4.3: Average number of codes by approach strategy

Code Frequencies by Strategy Group							
Strategy Group	**Sample Size**	**Average Number of Codes**	**Time to completion [minutes]**	**Average Number of KA Codes**	**Average Number of KG Codes**	**Average Number of SM Codes**	**Average Number of Answer Codes**
Plug and chug	2	10	5.07	1	3	2.5	1
Guess and Check	3	33. 33	20.72	1.67	13. 67	8	1
Segmentation	15	31.2	17.71	3.4	8.27	9.13	1.6
Chunking	4	21.25	14.32	2.5	5.75	5.75	1.5

Table 4.4: Average number of errors by expertise level

(as indicated by approach strategy)

Error Code Frequencies by Strategy Group					
Strategy Group	**Sample Size**	**Average Number of Conceptual Errors**	**Average Number of Mechanical Errors**	**Average Number of Management Errors**	**Probability of Success**
Plug and chug	2	1	0	1	0
Guess and Check	3	4	2	4.67	0
Segmentation	15	5.27	1	4.83	0.47
Chunking	4	3.5	2	3.33	0.63

Results indicate that those who used a plug and chug strategy were not successful but had the fewest number of codes, number of errors, and the shortest time to completion. This can be explained by limited awareness of performance problems. The other two novice groups (guess and check and segmentation groups), mirrored results identified in previous literature (Chi, et al., 1988) as characteristic of novice performance including longer time to completions, more errors, and a lower probability of success than the more expert level of performance (chunking group). Our results indicated faster completion time for more expert performance, though the results showed a more moderate difference between them and the more novice performance groups than what was observed in the research by Chi et al., namely four times faster. (Average completion times for "novice" groups, guess and check and segmentation, were 20.72 minutes and 17.71 minutes, respectively, compared to the "expert" performance group, chunking, which was14.32 minutes). Our research supports the claim that novices commit more errors; guess and check and segmentation groups committed an average of 10.67 and 11.1 errors respectively, compared to the chunking group, with an average of 8.83 errors. This indicates that this coding scheme provides a reasonable assessment of problem solving performance as indicated by relative expertise of the students.

CONCLUSION

This paper describes the methodology used to develop a robust coding scheme for the analysis of problem solving skills in a first year engineering program. Using this coding scheme, solutions were analyzed based on actions taken as a result of cognitive and metacognitive processes, which are categorized as knowledge access, knowledge generation, self-management, as well as errors (categorized as conceptual, mechanical, and management errors), approach strategies and solution accuracy. For our research, a mixed model methodology is used in order to assess problem solving skills levels by first quantitizing the data from students' written problem solutions. While the coding scheme was developed and validated using a set of well-defined story problems typical of a first year engineering course, because of the general nature of the categories of processes, errors, and strategies, it may be transferrable to other types of engineering problems that are more ill-defined or complex in nature.

Other researchers can use this methodology in their coding scheme development efforts for analyzing qualitative data related to complex processes. By following the procedure, we were able to ensure reliable coding among coders from different backgrounds and perspectives. However, it takes significant effort to train coders, and researchers should be leery about bringing in new coders unless there is a formal training and an assessment process to ensure consistency in coding. Ultimately, we chose to have one coder code all remaining solutions and the other coder review those coded solutions to ensure accuracy. While this step effectively doubled the time needed to the code data, the step was important for ensuring quality, even though relatively few edits were suggested by the reviewer following the training process.

This coding scheme is being used to assess problem solutions of first year engineering students at a large southeastern university. The process element, error, and strategy codes enable the assessment of various problem solving skills necessary to progress through the problem solving cycle. When the output of coded solutions is loaded into a database, the data can be queried in a number of ways to transform individual codes into meaningful measures of performance. That information can then be used to give insight to researchers and ultimately instructors and students. Using this information, the relationships between problem solving skills and students' academic preparation are being evaluated for its relationships to problem solving success and mental workload.

CHAPTER FIVE:

ESTABLISHING MEASURES OF PROBLEM SOLVING PERFORMANCE

As problem solving is an important skill for engineers to master, engineering educators should strive to help students obtain the knowledge and skills required for problem solving success. However, in order to assess the development of skills, it is necessary to be able to assess students' individual performances on a common set of criteria at various points in their studies. The purpose of this chapter is to establish a standardized method for assessing problem solutions in terms of performance based on activities involved in the problem solving process. The resulting list of performance measures will be used to evaluate student performance in a first year engineering course. In total, 28 internal process measures and 12 outcome measures were established.

INTRODUCTION

Performance assessment, the direct systematic appraisal of performance compared to a pre-determined set of criteria, have been shown to improve students' mathematical problem solving (Fuchs, Fuchs, Karns, Hamlett, & Katzaroff, 1999). Effective performance assessment requires that metrics be developed in order to compare processes of complementary entities (Damelio, 1995). While some instructors and even school systems have utilized performance assessments to measure students' problem solving competency, it is still not common practice. An initiative aimed at helping teachers develop performance assessments found that “time is a major obstacle to changing classroom practice” (Borko, Mayfield, Marion, Flexer, & Cumbo, 1997).

Research by Slater emphasizes the importance of performance assessment of problem solving skills, especially for STEM (science, technology, engineering, and mathematics) majors because it provides insight to a student’s level of conceptual and procedural knowledge (Slater, 1993). Slater states that the purpose of conducting performance assessments is “to evaluate the actual process of doing science or mathematics” (Slater, 1993, p. 3). It can be used for a variety of purposes including: 1) diagnostic purposes to determine what students know, 2) instructional purposes such as in class activities, or 3) monitoring purposes as through multiple iterations of evaluation to evaluate changes in skills. While Slater suggests performance assessment should be conducted with live evaluations of ill-defined tasks, there is no reason that performance assessment must be limited to this type of activity, where only one person or group can be evaluated at a time. His recommendation is in part due to the weaknesses of conventional paper and pencil assessments. However, by overcoming this barrier with technology that captures the entire problem solving process instead of a snapshot of the final solution (Bowman & Benson, 2010; Grigg & Benson, 2011), performance assessment can be applied to traditional learning activities for a larger population of students through evaluating archived data rather than live demonstrations.

ESTABLISHING MEASURES OF PROBLEM SOLVING PERFORMANCE

The remainder of this chapter details how the elements from the coding scheme, shown in Appendix D, were used to establish objective measures of performance throughout the problem solving processes. Using a mixed model methodology, problem solving performance was evaluated by quantitizing coded data from students' written problem solutions (Tashakkori & Teddlie, 1998). Problem solving was assessed along a seven stage cycle consisting of: 1) recognize / identify the problem, 2) define and represent the problem, 3) develop a solution strategy, 4) organize knowledge about the problem, 5) allocate resources for solving the problem, 6) monitor progress toward the goals, and 7) evaluate the solution (Pretz, et al., 2003).

However, in practice, there is much variability in how people approach the problem solving process. The proposed stages are not utilized by all problem solvers in all situations, and the problem solver may iterate between one or more stages as s/he responds to feedback (either internal or external) on progression toward solving the problem (Wilson, et al., 1993). Rather than viewing these stages as independent, it is more representative to think of them as concurrent subprocesses where actions taken in one subprocess may prompt action in another (Samsonowa, 2011, p. 27). This approach differs from models that evaluate problem solving as independent phases, such the Integrated Problem Solving (IPS) model, which can imply that students do not revise their initial understanding of the problem (phase 1) if the revisions occur after the student draws a picture, i.e. entered the second phase (Litzinger, et al., 2010).

In order to formulate performance measures for these problem solving processes, a variety of sources were investigated on measures of similar skills from the education and human performance literature. Measures were broken down into two forms: 1) internal process measures and 2) outcome measures. Internal process measures look at how thoroughly, accurately, and efficiently tasks are completed. Outcome measures evaluate whether the process is producing the desired results. By comparing internal process measures to outcome measures, one can determine which factors contribute to the desired results (Harmon, 2008).

MEASURES OF PROBLEM SOLVING PROCESSES

Education and human performance literature was utilized in determining measures that adequately evaluate student performance within the seven stages of Sternberg's problem solving cycle. Twenty-eight internal process measures were created and used to evaluate student problem solving attempts. Table 5.1 describes the breakout of the number of measures across stages. A complete list of developed metrics along with their calculation and measure type can be seen in Appendix E.

Table 5.1: Number of measures developed to assess problem solving processes

Problem Solving Stage		**Number of measures**
1	Recognize / identify the problem	3
2a 2b	Define the problem Represent the problem	3 3
3	Develop a solution strategy	1
4	Organize knowledge about the problem	5
5	Allocate resources for solving the problem	8
6	Monitor progress toward the goals	3
7	Evaluate the solution	2

Assessing Problem Recognition

Problem recognition (problem finding) is typically the earliest stage of problem solving as it orients the solver to the task (Pretz, et al., 2003). The way the problem is posed drives the problem solving process and will directly impact all subsequent processing (Getzels, 1979). In "presented problem situations," such as the ones under investigation in this research effort, the students are given the problem in written form (Getzels, 1975). Therefore, the problem recognition task is reduced to correctly identifying the problem within the given context. Problem recognition has been described as including lower level processing tasks such as inspection and interpretation of problem statements and given diagrams in order to formulate problem understanding and formulation of the goal (Litzinger, et al., 2010).

To assess problem recognition, three internal process measures were created. Equation 5.1 creates an indicator variable of whether there is an explicit statement of what the unknown variable is. Equation 5.2 creates an indicator variable of whether the student solved for the correct unknown value. Equation 5.3 evaluates the efficiency of problem recognition, such as whether the student was able to recognize the problem correctly initially or required multiple corrections. For this equation, and others like it, the error suffixed by "-HIT" represents that the error was identified and an attempt was made to correct that work. This basis for this distinction is explained in full in the section on "Assessing Progress Monitoring". All measures are shown in MS Access criteria statement format where "IIf" stands for "if and only if".

IIf([Identify unknowns]>0,1,0) (5.1)

IIf(Count([Incorrect unknown value]>0,0,1) (5.2)

IIf(Count([Incorrect unknown value]>0, "NA", Count([Incorrect unknown value-HIT])) (5.3)

Assessing Problem Definition and Representation

The second problem solving stage really consists of two processes used for the conceptualization of the system. The problem definition stage generally consists of information gathering which helps in understanding the problem. This consists of tasks such as situation assessment where the problem solver sets boundaries of what is included or excluded and interprets the situation (Smith, 1998). This stage might include tasks such as restating the problem, identifying assumptions, or identifying constraints.

To assess problem definition, three internal process measures were created. Equation 5.4 creates a count of the number of explicit problem definition statements. Equation 5.5 creates an indicator variable of whether the student correctly defined the problem. Equation 5.6 evaluates the efficiency of problem definition, such as whether the problem was correctly defined initially or required correction.

Sum(IIf(Count([Restate problem]>0,1,0)) + IIf(Count([Identify assumption]>0,1,0))+
IIf(Count([Identify constraint]>0,1,0))) (5.4)

IIf(Count([Ignored problem constraint]>0,0,IIf(Count([Incorrect assumption]>0,0,1))
(5.5)

IIf(Count([Ignored problem constraint]>0, “NA”, IIf(Count([Incorrect assumption]>0,
“NA”, Sum(Count([Ignored problem constraint -HIT])+ Count([Incorrect
assumption -HIT]))) (5.6)

Problem representation is recognized as an important step in the problem solving process (Jonassen, et al., 2006). A study of mathematical problem solving showed a positive correlation with schematic spatial representations, but a negative correlation with pictorial representations (Hegarty & Kozhevnikov, 1999). Therefore, the true value of diagrams may be to establish relationships between variables.

For assessing problem representation, four internal process measures were created. Equation 5.7 creates an indicator of the type of representation: no visual, pictorial, or spatial. Equation 5.8 creates an indicator variable of whether the student established correct relationships between variables. Equation 5.9 evaluates the efficiency of problem representation, such as whether the problem was correctly represented initially or required correction.

IIf([Draw a picture / diagram]>0, IIf([Relate variables]>0, 1,0.5),0) (5.7)

IIf(([Draw a picture / diagram]+[Relate variables])>0, IIIf(([Incorrect visual/graphic representation]+[Incorrectly relate variables])>0,0,1),0) (5.8)

IIf(Count([Incorrect visual/graphic representation]>0, “NA”, IIf(Count([Incorrectly relate variables]>0, “NA”, Sum(Count([Incorrect visual/graphic representation-HIT]) + Count([Incorrectly relate variables -HIT]))) (5.9)

Assessing Solution Approach Strategies

Novice and expert problem solvers use fundamentally different approaches to solving problems (Chi, et al., 1981). By stepping through the problem solving process, one can get a sense of how efficiently the problem solver moves toward the goal. However, methods used by experts to solve problems are not necessarily transferable to novices due to cognitive requirements necessary to use expert strategies (Wang & Chiew, 2010). Several heuristics (strategies) have been identified that can be used in classifying problem solving attempts in terms of strategy. Some common strategies include:

1) Problem Decomposition (segmentation) - which involves breaking down a complex problem to ease analysis (Nickerson, 1994).
2) Clustering (chunking) - which involves grouping like information into larger units (Chi, et al., 1981)
3) Means-End Analysis - which involves beginning with the identification of a goal state and the current state followed by the problem solver making efforts to reduce the gap between states (Nickerson, 1994).
4) Forward Chaining - which is similar to Mean-End Analysis but involves a direct path between the current state and goal state (Nickerson, 1994).

Some problems could also be classified according to an apparent lack of strategy.

5) Plug and chug - which involved inserting given values into an equation and producing an answer without necessarily understanding the reasons for doing so (Wankat, 1999).
6) Guess and Check - which is a slightly more sophisticated approach where the problem solver checks that the values inserted into an equation yields the correct units or checks for reasonableness of the solution (Wankat, 1999).

Plug and chug and guess and check strategies are considered beginner level strategies. Problem decomposition and means-end analysis strategies are considered intermediate level strategies while clustering and forward chaining are considered advanced strategies. Equation 5.10 depicts how the strategies are converted into quantized levels.

If ([Plug and chug], 0, IIf([Guess and check], 0, IIf([Segmentation],0.5, IIf([Means end analysis],0.5, IIf([Chunking],1, IIf([Forward chaining],1, "other")))))) (5.10)

Assessing Knowledge Organization

Experts organize their information differently than novices, utilizing larger chunking of information than novices (Larkin, et al., 1980a). Even with the same information (e.g. equations, real world objects, relations among objects, and quantities of variables needed to solve the problem), novices store the knowledge in an unorganized fashion, compared to experts (Elio & Scharf, 1990). One way for novices to reduce their cognitive load is to explicitly write down information to help them organize their knowledge (Brown & Duguid, 1998).

For knowledge organization, five internal process measures were created. Equation 5.11 creates an indicator of the number of knowledge organization tasks. Equation 5.12 creates an indicator variable of whether the student correctly identified known values. Equation 5.13 creates an indicator variable of whether the student correctly utilized the equation. Equation 5.14 evaluates the efficiency of recognizing known information while equation 5.15 evaluates the efficiency of recognizing equations, specifically whether this information was correctly identified initially or required correction.

Sum(IIf(Count([Identify known values]>0,1,0)) + IIf(Count([Identify equation]>0,1,0))) (5.11)

IIf(Count([Incorrect known value]>0,0,1) (5.12)

IIf(Count([Misuse governing equation]>0,0,1) (5.13)

IIf(Count([Incorrect known value]>0, “NA”, Count([Incorrect known value-HIT])) (5.14)

IIf(Count([Misuse equation]>0, “NA”, Count([Misuse equation -HIT])) (5.15)

Assessing How Resources are Allocated for Execution (Knowledge Generation)

During the problem solving process, it is important to manage cognitive resources effectively. However, people often rely on intuition in order to reduce the level of effort or use ineffective methods that increase cognitive effort. Striking a proper balance is essential in being able to properly execute the problem solving process and obtain a result that is well constructed and can be justified (Albers, 2005).

It is projected that documenting problem solving tasks will lead to fewer errors and lower mental workload. To test this, eight measures were developed to evaluate the performance of execution tasks. Equation 5.16 creates a count of the number of types of tasks used in the problem solving process that are used in transforming data. Equation 5.17 creates an indicator variable of whether mechanical tasks were executed properly. Equation 5.18 creates a count of how many tries it took to achieve correct mechanical execution of tasks. Equation 5.19 creates an indicator variable of whether the execution of tasks were managed properly. Equation 5.20 creates a count of how many tries it took to correct management execution errors.

Sum(IIf(Count([Manipulate equation]>0,1,0)) + IIf(Count(Derive Units]>0,1,0)) + IIf(Count(Use conversion factor]>0,1,0)) + IIf(Count(Plug values in equation]>0,1,0)) + IIf(Count(Document math]>0,1,0)) + IIf(Count(Solve intermediate value]>0,1,0))) (5.16)

IIf(Count([Incorrectly manipulate equation]>0,0, IIf(Count([Incorrect calculation] > 0, 0, IIf(Count([Incorrect unit derivation]>0,0,1)))) (5.17)

IIf(Sum(Count([Incorrectly manipulate equation]) + Count([Incorrect calculation]) + Count(Incorrect unit derivation]))>0, “NA”, Sum(Count([Incorrectly manipulate equation-HIT]) + Count(Incorrect calculation-HIT]) + Count(Incorrect unit derivation-HIT]))) (5.18)

IIf(Count([Inconsistent transcription]>0,0, IIf(Count([Inconsistent units]>0,0, IIf(Count([Incorrect unit assignment]>0,0, IIf(Count([Missing units throughout]>0,0,1)))) (5.19)

IIf(Sum(Count([Inconsistent transcription]) + Count([Inconsistent units]) + Count([Incorrect unit assignment]) + Count([Missing units throughout]))>0, NA, Sum(Count([Inconsistent transcription-HIT]) + Count([Inconsistent units-HIT]) + Count([Incorrect unit assignment-HIT]) + Count([Missing units throughout-HIT])) (5.20)

Some research suggests that more simplistic streams of processes (fewer transitions between types of elements) is related to problem solving success (Stahovich, 2012). The number of elements can serve as proxy for the number of transitions as shown in Equation 5.21. Another means of measuring how efficient one allocates resources is to count inefficiencies such as extraneous cognitive processing, which is characterized by utilizing inappropriate approaches or using irrelevant information.

Mayer suggests that educators should work to minimize extraneous processing, manage essential processing, and foster generative processing (Mayer, 2008). Two such measures of extraneous processing include the use of irrelevant information and incorrectly erasing correct work as depicted in Equations 5.22 and 5.23 respectively.

$$\text{Count[Task]} \tag{5.21}$$

$$\text{Count([Irrelevant Information])} \tag{5.22}$$

$$\text{Count([Erasing correct work])} \tag{5.23}$$

Assessing Progress Monitoring Using Signal Detection Theory

Lack of awareness of performance errors has been shown to be one of the key indicators of differences in novice and expert solutions (Chi, et al., 1981). Recent studies on problem solving have attempted to assess monitoring by counting the instances of performance error detection, reworking a part of the problem or expressing confusion or awareness of a challenge (Litzinger, et al., 2010). However, this measure gives a skewed representation of monitoring because those who make more errors have more opportunities to detect and self-correct errors.

Assessment measures should allow comparison between students and a standard that represents expected competency level. Standardized measures exist in human performance literature that provide scores that are adjusted to account for process variations such as different number of errors. Using Signal Detection Theory, error detection can be measured, as a proxy for monitoring, in a way that enables comparison between solutions either across people or across assignments. Signal Detection Theory, was first described by Green and Swets to evaluate a decision maker's performance detecting a signal when there was unpredictable variability present (Green & Swets, 1966). Since then, the theory has been utilized in a range of contexts including measuring the ability to recognize stimuli such as tumors in medical diagnostics or weapons in air travel luggage scans (Macmillan & Creelman, 2005). Recent work in education has used Detection Theory to analyze rater behavior in essay grading and assessment of student abilities (Abdi, 2009). Detection Theory quantifies the reaction of an observer to the presentation of a signal in an environment containing noise as one of four classifications based on whether the stimuli was present or not and whether the observer responded as if the stimuli was present or not.

Measuring error detection in student work can be done by classifying problem solving activities as one of four states: 1) HIT is when there is an error and the student recognized an error, 2) MISS is when there is an error and the student does not recognize the error, 3) FALSE ALARM is when there is not an error but the student identified it as having an error, and 4) CORRECT REJECTION is when there is no error and the student correctly does not recognize an error. Table 5.2 illustrates the error monitoring states given error present and error absent conditions.

Table 5.2: Matrix of State Possibilities for Error Present and Error Absent Situations

	Error Present	**Error Absent**
Error Identified	Hit	False Alarm
No Error Identified	Miss	Correct Rejection

Temporal (fuzzy) signal detection theory (Parasuraman, Masalonis, & Hancock, 2000) is utilized to accommodate the temporal variability present between the arrival of a signal (an error that is committed) and the detection of the signal (modifying work in which the error is present). Here, the number of hits, misses, false alarms, and correct rejections would be reassessed at each opportunity for an evaluation. For example, if a student makes an error at t=30 seconds, that error would be classified as a MISS and if the error is later correct at t=45 seconds, then it would be reclassified as a HIT. This process would continue until the end of the solution.

Using this information, a measure of sensitivity can be calculated for the student as a measure of error detection performance. Sensitivity (d') measures the ability to distinguish between the signal and the noise, or in the case of error detection, to identify only errors that are truly errors. Sensitivity is measured by the proportion of hits minus the proportion of false alarms where hits are defined as recognizing an error that was truly made and a false alarm is identifying an error that was actually not an error. The nonparametric equivalent for sensitivity is A’, which was first described by Pollack and Norman in 1964 (Craig, 1979). The equation for A’ is shown in calculation 5.24 and equations 5.25 and 5.26 show how to calculate the false alarm rate and hit rate needed to assess sensitivity. The measure yields a value between 0 and 1 with scores similar to the typical grading scale with 1.0 indicating perfect detection, 0.7 indicating fair detection, 0.5 indicates no discrimination, and values below 0.5 typically indicate an error of some kind either confusion on the task or miscalculation by the researcher.

$$A' = 1 - \frac{1}{4}\left[\frac{P(FA)}{P(H)} + \frac{1-P(H)}{1-P(FA)}\right] \tag{5.24}$$

$$P(FA) = \frac{\#FALSE\_ALARM}{\#FALSE\_ALARM + \#CORRECT\_REJECTIONS} \tag{5.25}$$

$$P(H) = \frac{\#HIT}{\#HIT + \#MISS} \tag{5.26}$$

Assessing Solution Evaluation

The final problem solving step is to check the accuracy of the final answer. No matter what the level of expertise, mistakes can be made, and it is important to check that the answer is reasonable through techniques such as estimating what the answer should be or reworking calculations. To assess a student checking accuracy, two internal process measures were created. Equation 5.27 creates an indicator variable of whether there is explicit work that documents checking work, such as rework following solution, an estimation, or other similar task. Equation 5.28 creates an indicator variable of whether there is an explicit indication of what the final answer is. While not an explicit check for accuracy, it is a verification that the final answer was reached.

IIf([Check accuracy]>0,1,0) (5.27)

IIf([Identify final answer]>0,1,0) (5.28)

MEASURES OF PERFORMANCE OUTCOMES

Traditionally, instructors evaluate students' solutions based on the accuracy of the final answer. Sometimes other considerations come into account such as whether the student indicates confidence in their answer (Szetela, 1987). However, other measures can be used to evaluate the solution in terms of process efficiency and student stress levels following completion of the task. Twelve outcome measures were created and used to evaluate the resulting outcomes of student problem solving attempts. Table 5.3 describes the breakout of the number of measures across each entity (Jablokow, 2007). A complete list of developed metrics along with their calculation and measure type can be seen in Appendix F.

Table 5.3: Number of measures developed to assess problem solving outcomes

Problem Solving Stage		Number of outcome measures
1	Solution accuracy	4
2	Attempt efficiency	2
3	Student stress levels	6

Assessing Solution Accuracy

Outcome measures describe the person's effect on the task (Drury, 1990). For the problem solving tasks, outcomes are assessed for both the accuracy of the final solution and efficiency of the problem solving attempt. For assessment of accuracy, four assessment measures are used. Equation 5.29 shows that the accuracy of the solution is evaluated in terms of the final answer or average of answers for multipart problems. First, each answer is classified as correct, correct with missing units, incorrect, or gave up and the code is transformed into a numeric equivalent (correct answer = 1, correct but missing units = 0.5, incorrect and gave up = 0). For additional measures of accuracy, three types of errors were evaluated based on the number of errors that remained in the final solution. Conceptual errors (Equation 5.30) describe instances of misunderstanding the problem and/or underlying fundamental concepts. Mechanical errors (Equation 5.31) describe instances of operation errors such as an incorrect calculation or a flaw in deriving units. Management errors (Equation 5.32) describe instances of mismanaging information while identifying given information, transcribing values, assigning units, etc.

Average [Answer State] (5.29)

Count[Conceptual Errors (not corrected)] (5.30)

Count[Mechanical Errors (not corrected)] (5.31)

Count[Management Errors (not corrected)] (5.32)

Assessing Attempt Efficiency

For assessing of the problem solving attempt, two measures were created based on human performance literature. The error rate serves as a measure of human reliability by indicating the frequency of occurrence of quality problems (Equation 5.33).

The time to completion, equation 5.34 is a performance measure traditionally used to assess human performance, as often accuracy is compromised in favor of speed (Drury, 1990).

$$\frac{\text{Count}\left[\text{Errors}\right]}{\text{Count}\left[\text{Tasks}\right]} \tag{5.32}$$

[End time]-[Start time] (5.33)

Assessing Stress Measures

The final outcome measure is the impact of the task on the student. This is measured in terms of the students' mental workload. If cognitive resources are adequate during the completion of the task, mental workload would be lower than if resources were inadequate. While there are several methods for assessing mental workload, one of the best methods in terms of ease of data collection and analysis is using a standard self-report measure such as the NASA-TLX (Hart, 2006). The NASA-TLX consists of six subscales, three measuring demand put on the participant by the task and three measuring stress added by the worker because of interacting with the task. The three measures of task demand include 1) mental demand, 2) physical demand, and 3) temporal demand. The remaining measures, 4) effort, 5) performance, and 6) frustration, describe the stress put on the person by the interaction of the person with the task (Warm, et al., 2008); however, physical demand is irrelevant for cognitive tasks and can be excluded from analysis. The NASA-TLX subscales are scored on a continuous scale from zero to twenty (Stanton, et al., 2005). Using this scale, a measure of workload can be calculated by summing the values from individual subscores as shown in Equation 5.35. However, the individual subscale scores can also be used as indicators of specific stressors.

Sum([Mental Demand]+[Temporal Demand]+[Performance]+[Effort]+[Frustration]) (5.35)

These measures will serve as a means of comparing problem solving performance in subsequent investigations. In Chapter 6, internal process measures are used in the comparison of correct and incorrect solutions. In Chapter 7, internal process measures are used in the comparison of outcome measures of mental workload. In Chapter 8, internal process measures and outcome measures are used in the comparison of participant factors including, gender, ethnicity, and prior academic experience. Relationships are explored further in Chapter 9, which offers final recommendations on the usefulness of measures in providing feedback to students on their problem solving performance.

CHAPTER SIX

WHAT PROBLEM SOLVING FEATURES ARE MORE PREVALENT IN SUCCESSFUL SOLUTIONS?

This investigation looks at enhancing research-based practice in higher education by exploring what problem solving features and student actions are related to successful problem solving attempts. The primary goal of this investigation was to compare successful and unsuccessful solutions in terms of cognitive and metacognitive processes, errors, and strategies, to elucidate key findings that can be incorporated into performance evaluations of student work. Data from two semesters were included in this analysis. In the first semester (n=27), students solved problems using their method of choice; however, in the second semester (n=36), another cohort of students were asked to use planning and visualization activities. As a secondary goal, this study evaluates the effectiveness of this pedagogical intervention on improving problem solving performance in the classroom. Variation in success across semesters was used as a proxy measure of the effectiveness of this instructional intervention.

Results indicated that implementing the problem solving structure had a positive impact on problem solving success. Additionally, statistical analysis of solution data revealed that correct solutions were more likely to contain instances of 1) explicit planning activities such as identifying unknown values and conversion factors, 2) explicit manipulation of variables when converting between units, and 3) evidence of a means-ends-analysis approach to solving the problem. There were also significant effects on problem solving success from using conversion factors, documenting math, and utilizing a chunking strategy to approach the problem, all of which were associated with correct solutions. Incorrect solutions were more likely to contain instances of 1) implicit equation identification, 2) ignoring problem constraints, 3) identifying errors, and 4) evidence of a plug-and-chug approach to solving the problem. There were also significant effects on problem solving success from labeling/renaming, incorrectly relating variables, and inconsistent units, which were associated with incorrect solutions.

Next, performance measures were assessed to determine their ability to discriminate between actions associated with successful versus unsuccessful solutions. Sixteen of the twenty-eight proposed performance measures of processes were able to distinguish between successful and unsuccessful problem solving attempts. This information gives insight into the effectiveness of different strategies that novice problem solvers use to manage the problem solving process. The ultimate goal of this project is to inform the development of problems and instructional pedagogies for introductory engineering courses which capitalize on successful strategies.

INTRODUCTION

Learning does not occur as a passive action. For meaningful learning to occur, one must make sense out of newly presented information and form connections with relevant conceptual knowledge in order to anchor new ideas (Novak & Gowin, 1984). When this prior conceptual knowledge is lacking or inappropriate, rote learning or memorization may occur, which involves retention with little or no comprehension or transferability (Barnett & Ceci, 2002). In problem-based learning scenarios, students are able to apply their newly acquired conceptual knowledge to example scenarios, which help construct an interpretation of the concepts and anchor that information along with a context for which the information can be utilized in the future.

However, gaps in a student's framework of relevant concepts and inferior problem solving skills can greatly influence how efficiently and successfully a student can solve problems in the intended manner (Chi, et al., 1981). Research has shown that novice problem solvers often employ weak, self-defeating strategies. For example, novices often jump into solving word problems or manipulating datasets, immediately attempting to find solutions by plugging numbers into equations with little focus on analyzing the problem state or considering effective, strategic courses of action (Chi, et al., 1981). Given enough time, students may successfully solve problems through inefficient methods, such as using a "plug and chug" approach or "pattern matching" based on previously completed work with little understanding as to why the solution approach is appropriate (Nickerson, 1994).

While there is much research that identifies differences between novice and expert problem solvers (Chi, et al., 1981; Elio & Scharf, 1990; Larkin, et al., 1980a) , it has also been shown that many of the techniques that experts use are not feasible for use by novices because of limitations of their cognitive processing capabilities (Wang & Chiew, 2010). There is little evidence describing what strategies novices can use to help improve their performance and build skills.

Many instructors have encouraged the use of planning and visualization activities for students to overcome some of the hindrances experienced by novice learners. Intuitively, it seems like getting key information on paper will make the information easier to manage, maybe even help with forming connections between the material. However, the true impact of these activities on problem solving success is not well documented, and practitioners mostly rely on anecdotal evidence that it seems to help. Some commonly suggested planning include 1) review the problem and clarify meaning, 2) define the problem, 3) identify given knowledge, 4) identify the knowledge needed to acquire, and 5) set objectives (Nilson, 2003). Problem representation has also been cited as an important step in the problem solving process (Jonassen, et al., 2006). However, a study of mathematical problem solving showed variability between the effectiveness of representations depending on whether the diagrams are simply pictorial or whether they are spatial representations, with spatial representations being correlated with higher success (Hegarty & Kozhevnikov, 1999).

The goal of this investigation was to identify whether the use of planning and visualization strategies improved problem solving performance and to identify features of problem solutions that were associated with successful problem solving attempts in a first year engineering course. This information enables researchers to identify best practices and can be instrumental in the development of effective instructional interventions aimed at improving problem solving performance of novices.

METHODS

Data was collected during two separate course offerings. The samples of problem solving attempts were collected from in-class activities completed by students as part of the normal conditions for class. In the first semester, Fall 2009, students solved problems in whatever manner they felt best; however, in the second semester, Spring 2011, students were encouraged to use information organization strategies and draw diagrams to promote problem solving success. Specifically, students were asked to 1) restate the problem in their own words, 2) identify known values, 3) identify the unknown value, 4) identify key equations, and 5) draw a diagram to represent the problem. Data were collected for 27 students in Fall 2010 and 36 students in Spring 2011 for three different problems each semester.

Technology Used to Capture the Problem Solving Process

Problem solving data were obtained via students' completed in-class exercises using a program called *MuseInk*, developed at Clemson University (Bowman & Benson, 2010; Grigg & Benson, 2011). This software was used in conjunction with tablet computers that were made available to students during the class period. Students worked out problems in the *MuseInk* application, which digitally records ink strokes and keeps a running log of the entire solution process from beginning to end, including erasures, and can be replayed and coded directly in the application at any point in time.

Engineering Problems

The three problems analyzed covered the topics of 1) efficiency, 2) circuits, and 3) pressure. All problems had 1) a constrained context, including pre-defined elements (problem inputs), 2) allowed multiple predictable procedures or algorithms, and 3) had a single correct answer (Jonassen, 2004). All three problems were story problems, in which the student is presented with a narrative that embeds the values needed to obtain a final answer (Jonassen, 2010). The first problem involved a multi-stage solar energy conversion system and required calculation of the efficiency of one stage given input and output values for the other stages (Stephan, Park, Sill, Bowman, & Ohland, 2010). The second problem required students to solve for values of components in a given electrical circuit. This problem, developed by the project team, also contained a Rule-Using/Rule Induction portion (a problem having one correct solution but multiple rules governing the process (Jonassen, 2010)), where students were asked to determine an equivalent circuit based on a set of given constraints. The third problem involved hydrostatic pressure in a vessel, and required students to solve for values within the system, and convert between different unit systems (Stephan, et al., 2010). The problems are included in Appendices A-C.

Statistical Analysis Methods

Solutions were analyzed using a validated coding scheme, which classified the problem solving processes based on relevant events. For codes related to process elements, the basic structure of the coding scheme was based on a study of mathematical problem solving, with categories of knowledge access, knowledge generation, self-management (Wong, et al., 2002). For codes relating to errors, a structure derived from error detection literature in accounting was used to classify errors as conceptual and mechanical errors (Owhoso, et al., 2002; Ramsay, 1994), with an added classification of management errors to capture errors in metacognitive processes. Strategy codes were obtained from a subset of strategies that appeared most applicable to story problems from the compilation described in "Thinking and Problem Solving" (Nickerson, 1994). A description of codes can be found in Appendix D.

Evaluation of the Effects of Problem Solving Features on Success: Statistical analyses were conducted to identify variations between successful and unsuccessful solutions in terms of the presence of problem solving elements. Further statistical analyses were conducted to evaluate whether measures of problem solving performance were able to discern between correct and incorrect solutions. Finally, post-hoc analyses were conducted to verify that variations in performance were not due to mathematical abilities as measured by three standardized tests.

As a primary investigation, Chi Square tests were conducted to test whether differences in proportions were larger than due to chance. All problem solving features occurring at least once in the problem solving attempts were classified as occurring, even if the work was later modified to eliminate its presence in the final solution. Then, odds ratios were calculated to determine how much more likely a successful or unsuccessful solution was to contain a particular feature. For this analysis, each solution was treated as an independent sample to approximate general trends.

A secondary analysis was conducted in order to evaluate the predictive value of specific problem solving features on problem solving success while taking into account anomalies that may have occurred because solutions were not independent samples, as the same student completed up to three solutions. Linear mixed-effect models were used to verify the relationships to problem solving success after accounting for variations due to the problem, the semester, and the participant. The factor of "semester" is being used as a proxy measure of the effect of the pedagogical intervention in the second semester.

Evaluation of Performance Measures and their Relationships to Problem Solving Success: In an effort to validate the proposed performance measures, statistical analyses were conducted to evaluate whether the transformed data was associated with and able to predict successful solution outcomes. Twenty-eight internal process measures of students' problem solving methods and skills utilized along Sternberg's seven stage problem solving cycle were evaluated (Pretz, et al., 2003). Five outcome measures were also evaluated as a means of validating that they are acceptable predictors of success. Performance measures and their calculations are included in Appendix E.

Similar to the analysis methods of problem solving features, Chi Squared tests were conducted to compare differences in performance measures of categorical nature and Wilcoxon sum rank tests were conducted on performance measures that were of interval or ratio data types, using the Chi Squared approximation to determine the level of significance. As before, repeated measures analyses were conducted using linear mixed-effects models to assess the predictive strength of performance measures after taking into account effects due to the problem, semester, and the participant.

RESULTS

Effects of Planning and Visualization Activities

Results indicated that problem solving success was improved by encouraging information organization and problem representation tasks, as there was a significant increase in the success rate for the semester when the intervention occurred ($p=0.001$). During the Fall 2009 semester, when students completed problems in their preferred manner, only 21% of solutions were 100% correct. During the Spring 2011 semester, when students were encouraged to use information organization and problem representation strategies, 80% of solutions were 100% correct.

An analysis of problem definition and representation strategies present on the Spring 2011 data in isolation showed significant effects on successful solutions when planning tasks were completed in the first half of the solution attempt (Grigg & Benson, 2012). Results revealed that when students completed a planning phase that involved restating the problem, identifying known values, identifying the unknown value, and explicitly identifying relevant equations during the first half of their problem solving attempt (n = 28 of 76), solutions were more likely to include correct answers (p = 0.05). Figure 6.1 illustrates the use of a complete planning phase and the resulting correct solution while Figure 6.2 illustrates an incomplete planning phase and the resulting incorrect solution. Unfortunately, this analysis cannot be compared with the Fall 2009 data, as no one completed all of the problem definition tasks by choice.

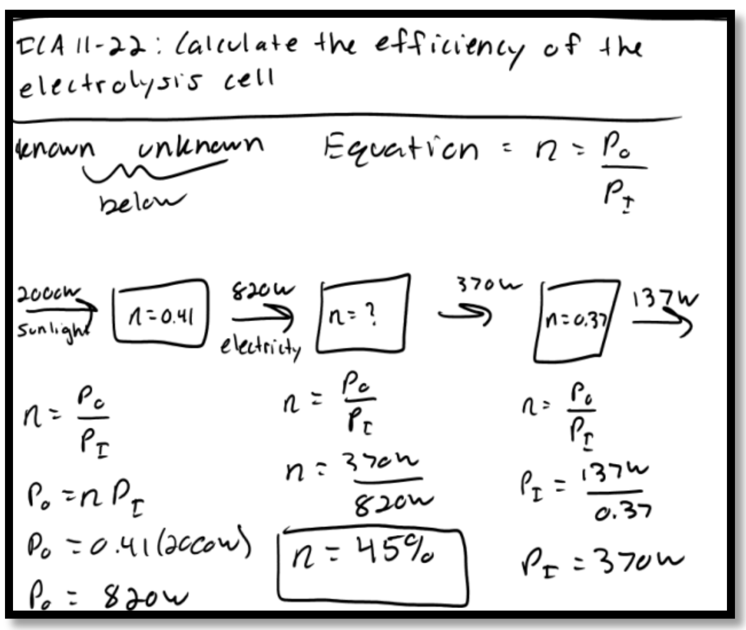


Figure 6.1: A correct solution utilizing a complete planning phase: restating the problem, identifying known values, identifying unknown values, and identifying equations

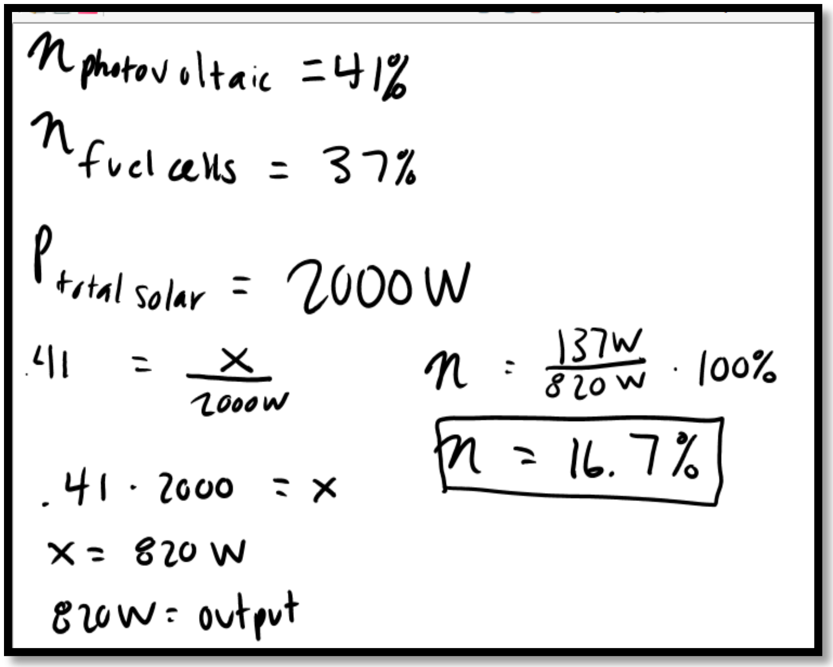


Figure 6.2: An incorrect solution, which utilized an incomplete planning phase including only identifying some known values.

Prominence of problem solving features in correct versus incorrect solutions

Based on the analysis of Chi Squared tests and odds ratios, problem solving attempts that resulted in correct solutions were more likely to contain instances of 1) identifying known values, 2) identifying unknown values, 3) identifying or using conversion factors, 4) deriving units 5) identifying the final answer, and 6) utilizing a means-end analysis strategy to solve the problem. However, they were also more likely to contain instances of incorrect unit assignments. Problem solving attempts that resulted in incorrect solutions were more likely to contain instances of 1) implicit use of equations (rather than explicitly stating the equation), 2) identifying errors (due to a larger number of errors committer such as ignoring problem constraints), 3) ignoring problem constraints, and 4) utilizing a plug-and-chug strategy. Table 6.1 depicts the significant results from the collection of all problem solutions. A complete evaluation of odds ratios is included in Appendix G, both from the overall perspective and each problem separately.

Table 6.1: Significant Relationships found from the Assessment of Odds Ratios for Fall 2009 and Spring 2011 collectively

	Chi Squared	**P value**	**Odds Ratios: Correct solutions were * times more likely to contain**	**Odds Ratios: Incorrect solutions were * times more likely to contain**
Identify known values	4.070	0.0436	2.09	0.48
Identify unknown value	25.096	0.0001	6.27	0.16
Identify conversion factor	7.698	0.0055	6.72	0.15
Use conversion factor	5.663	0.0173	2.36	0.42
Derive units	5.900	0.0151	2.70	0.37
Identify final answer	4.469	0.0345	2.35	0.43
Incorrect unit assignment	4.337	0.0373	3.71	0.27
Means-end analysis	13.831	0.0002	8.14	0.12
Implicit equation identification	19.079	0.0001	0.21	4.66
Identify errors	4.463	0.0346	0.22	4.65
Ignored problem constraints	6.261	0.0123	0.24	4.21
Plug and chug	26.842	0.0001	0.08	12.41

Next, problem solving features were evaluated using linear mixed-effects models to calculate the significant effects on success while taking into account variability attributable to the problem, and the semester as well as random effects of the person. While it was expected that a majority of the significant effects would mimic those observed via Chi Squared tests, only two of the effects of problem solving tasks and two of the effects of strategies remained the same. It was evident that the problem and the semester had significant effects on all analyses, with the second problem being associated with lower success rates and the second semester (the intervention group) being associated with higher success rates. Based on the regression models, additional problem solving features associated with successful solutions included 1) documenting math and 2) utilizing a chunking strategy. Additional problem solving features associated with incorrect solutions included 1) labeling and renaming, 2) incorrectly relating variables, and 3) inconsistent units. The use of problem solving features such as identifying known values, identifying unknown values, and identifying conversion factors were likely attributed to effects of the semester rather than success as most all students in the second semester utilized those features and were no longer found to have significant effects. The additional significant effects found for errors were likely associated with specific problems, and were not found to be significant until the effects of the problems were taken into account. A summary of significant effects is shown in Table 6.2 and a detailed description of the linear mixed-effects models is included in Appendix H.

Table 6.2: Summary of significant effects influencing problem solving success

Arrows indicate the directionality of the effect. Up arrows indicate positive correlations with success (100% correct solutions) and down arrows indicate negative associations.

Problem Solving Features		Problem Solving Success
Tasks	Use conversion factor	↗
	Document math	↗
	Labeling / Renaming	↘
	Identify errors	↘
Errors	Incorrectly relate variables	↘
	Inconsistent units	↘
Strategies	Plug and Chug	↘
	Means-ends-analysis	↗
	Chunking	↗

Are the Performance Measures Predictive of Problem Solving Success?

When correct and incorrect solutions were compared in terms of internal process measures of performance, several significant findings emerged that indicated which actions were associated with problem solving success. Findings showed that explicitly identifying the unknown value, explicitly (and correctly) defining the problem, and explicitly writing out known values and equations were all related to correct solutions. In addition, using intermediate or advanced level strategies, rather than strategies of guess and check or plug-and-chug, were related to correct solutions. Utilizing more knowledge generation tasks, executing correct mechanical manipulations, and indicating the final answer were also related to correct solutions; however it was also related to a more problem elements overall. One of the most highly correlated performance measures was the accuracy of identifying errors as measured through the hit rate and sensitivity scores. Table 6.3 reports the findings of the tests of process measures along with the mean values and significance level of differences. Four of the five outcome measures had significant effects in association with success. Management errors and time to completion did not have significant relationships to success. Table 6.4 reports the findings of the tests of outcome measures along with the mean values and significance level of differences.

Next, performance measures were evaluated using linear mixed-effects models to calculate the significant effects on success while taking into account variability attributable to the problem and the semester, as well as random effects of the person. Eight of the relationships disappear when accounting for effects of differences across semester and random effects of the person. Four additional significant effects emerged. The shift appeared to navigate away from the significant effects of explicit expressions in favor of correct execution of those tasks. This indicates that the explicit expression of tasks may be more useful for specific individuals, but overall, the accuracy of those expressions is most significant to problem solving success. In addition, relationships between success and all outcome measures were significant except for time to completion. A summary of significant effects are shown in Tables 6.5-6.6 and the extended results are shown in Appendices I-J.

Table 6.3: Collective Assessment of internal process measures of performance for Fall 2009 and Spring 2011 combined

	Process Analysis Measure	Chi square	p value	Mean (Correct)	Mean (Incorrect)
Recognize / identify the problem	Explicit unknown value	25.096	0.001	64.63%	22.58%
	Correct Unknown value	0.041	0.840	92.68%	93.55%
	# Tries to get correct unknown	3.69	0.057	0.12	0.03
Define the problem	Explicit definition	17.590	0.001	41.46%	14.52%
	Correct definition	8.225	0.004	98.78%	87.10%
	# Tries to get correct definition	2.252	0.133	0.04	0.13
Represent the problem	Explicit visual	0.737	0.692	42.68%	38.71%
	Correct representation	3.637	0.057	46.34%	30.65%
	# Tries to get correct representation	0.500	0.479	0.45	0.42
Develop a strategy	Approach Strategy Used (above basic)	22.369	0.001	91.46%	58.06%
Organize knowledge about the problem	Explicit knowns and equations	6.256	0.012	85.37%	74.19%
	Correct known values	0.305	0.581	91.46%	88.71%
	Correct equation	2.851	0.091	93.90%	85.48%
	# Tries to get correct knowns	3.560	0.059	0.13	0.05
	# Tries to get correct equation	1.319	0.252	0.35	0.19
Allocate resources (Execution)	Execute tasks to arrive at solutions	5.447	0.020	3.63	3.13
	Correct Execution-Mechanical	7.299	0.007	97.56%	85.48%
	# Tries to get correct mechanical	2.349	0.125	0.33	0.13
	Correct Execution-Management	0.176	0.675	74.39%	77.42%
	# Tries to get correct management	3.836	0.050	0.41	0.16
	Number of tasks	9.200	0.002	23.91	21.26
	Overprocessing (Erasing correct work)	0.699	0.951	68.29%	70.97%
	Overproduction	6.233	0.284	78.05%	83.87%
Monitor progress toward goals	Sensitivity (A’)	48.841	0.001	0.92	0.73
	Hit rate	52.883	0.001	0.76	0.32
	False alarm rate	0.051	0.822	0.025	0.026
Evaluate the solution	Check accuracy	0.218	0.641	8.54%	6.45%
	Indicate answer	4.469	0.035	84.15%	69.35%

Table 6.4: Collective Assessment of outcome measures of performance for Fall 2009 and Spring 2011 combined using Chi Squared Tests

Outcome Measure	Chi square	p value	Mean (Correct)	Mean (Incorrect)
Conceptual Errors	14.521	0.001	0.16	0.58
Mechanical Errors	7.336	0.007	0.02	0.17
Management Errors	1.337	0.248	1.21	1.50
Error Rate	20.157	0.001	0.15	0.26
Time to completion	1.827	0.177	20.40	18.87

Table 6.5: Summary of Significant effects from Regressions of Process Measures on Success using Linear Mixed Effects Model

	Process Measure	Success
Represent the problem	Correct representation	↗
Develop a solution strategy	Approach Strategy Used	↗
Organize knowledge about the problem	Correct known values	↗
	# Tries to get correct known values	↗
Allocate resources (Execution)	Correct Execution - Mechanical	↗
	Correct Execution - Management	↗
Monitor progress toward the goals	Sensitivity (A’)	↗
	Hit rate	↗

Table 6.6: Summary of Significant effects from Regressions of Outcome Measures on Success using Linear Mixed Effects Model

Outcome Measure	Success
Conceptual Errors	↘
Mechanical Errors	↘
Management Errors	↘
Error Rate	↘

DISCUSSION

There was a dramatic improvement in the problem solving success rate of students in the Spring 2011 semester, who were asked to utilize information organization and visualization tasks, over the Fall 2009 semester, where students were left to construct problem solutions as they saw fit. When comparisons were made that accounted for random effects of the students and fixed effects of the problem and the semester, the semester was a significant indicator of success at the $p < 0.001$ level. At first, it was believed that there might have been a discrepancy between semesters with the intervention group having more advanced mathematics skills. However a post hoc review of standardized test scores on the SAT math portion, CMPT (Clemson Math Placement Test), and BST (Basic Skills Test) showed that the intervention group actually had lower average test scores for the SAT math portion ($p=0.009$) and the CMPT ($p=0.009$) and there was not a statistically significant difference between groups on the

BST. Therefore, the more successful problem solving performance was not likely to be due to mathematics skills, reaffirming that there was, indeed, a positive impact from of implementing this problem solving structure.

Comparisons of student problem solving attempts revealed that explicitly writing out information seemed to improve the chances of achieving correct solutions for many students. Yet, when variability due to the student was taken into account, the accuracy of the information was more closely related to success. It is possible that, in some cases, simply going through the task of identifying information oriented students to the solution path. On a related note, some students were able to overcome errors (especially management errors) to arrive at correct solutions despite the errors evident in their solutions; however, this was highly dependent on effects of the student. On the other hand, more detrimental effects occurred from conceptual or mechanical errors. It also appears that some students need to rely on writing out each step of their algebraic manipulations (documenting work) more than others do, as this effect disappears when random effects of the student are taken into account.

Correct visual representations of the system were also found to be associated to problem solving success when taking into account effects of the problem, semester, and students, though these factors all play a role in how useful the diagram is. It is important to note that correct visual representations were considered only for those that established correct relationships between variables in addition to a pictorial aspect.

It was also revealed that making errors (especially incorrectly relating variables, ignoring problem constraints, or having inconsistent units within the documented work) were associated with incorrect solutions. However, simply making an error did not necessarily lead to an incorrect solution, as many students who achieved correct solutions made errors, but were able to correct them, even if it took multiple attempts. In fact, one of the most significant factors in problem solving success were the measures of sensitivity and hit rate, or the correct identification of errors. Therefore, instructors have an opportunity to help students enhance problem solving performance by encouraging the development of error identification skills.

Another key differentiator between correct and incorrect solutions was the approach taken to solving the problem. While a chunking strategy was associated with correct solutions, the approach may not be practical for all students as it is considered an advanced strategy; novice problem solvers may not have the cognitive resources to employ this strategy. However, means-ends-analysis, considered an intermediate strategy, was also highly correlated to problem solving success, while a plug-and-chug strategy, a lower level strategy, was highly correlated to incorrect solutions. This highlights the need for instructors to work with students on developing plans for the execution of problem solving tasks.

CONCLUSION

This research suggests some techniques that instructors may use to encourage problem solving success. Encouraging planning activities had a positive impact on student problem solving success for the problems included in this analysis. However, instructors should emphasize the benefits of restating the problem in their own words before identifying known values, unknown values, and equations. The interconnectivity of these processes should be emphasized. Students may also benefit from returning to restate the problem as a means of overcoming impasses or errors in the problem solving attempts as errors made in the planning phase can have detrimental effects throughout the remainder of the solution. On a related note, instructors should also emphasize error identification.

While many instructors may be eager simply to instruct students to utilize these techniques, students will likely resist unless there is a formal explanation of the benefits. For example, students in the Spring 2011 semester often restated the problem, identified known values, identified the unknown values, and identified relevant equations after completing the problem simply to fulfill those requirements, reducing the effectiveness of the planning activity (and likely also reducing the statistical power assigned to those codes in this analysis). Only 36.8% of solutions utilized the planning activities as intended despite over 70% of students eventually completing the tasks. It is suggested that instructors explicitly teach problem solving methods to inform students of the value of these planning activities rather than simply requiring their use to have the greatest impact on student learning.

One possible way of encouraging these planning activities and development of error identification skills is to conduct an in-class activity where students detail the system from different problems and swap the problem setups with other students who in turn evaluate the setups for accuracy (independent of knowledge generation tasks). An alternative is for instructors to break down the problem into multiple parts, where students have to transition through the problem solving process as they progress through the problem. For example, having "Part A" to define and represent the problem, before transitioning into "Part B" where students execution tasks to solve for the unknown value and "Part C" where students reflect on their answer and justify their method and/or solution. Leading the student through a multi-step solution may help teach students how they should approach problem solutions. However, this strategy would likely be most effective if students were made aware of the purpose of the guided solution and would be most effective when taught in conjunction with problem solving strategies. In this situation, instructors can explicitly address problems in student methods by assessing their problem solving skills on performance measures such as those utilized in this manuscript. Receiving a record of problem solving skills deficiencies may help students raise metacognitive awareness and serve to pinpoint areas of instructional need. The development of a rubric for this purpose is discussed in Chapter 9.

CHAPTER SEVEN

WHAT ARE THE RELATIONSHIPS BETWEEN PROBLEM SOLVING PERFORMANCE AND MENTAL WORKLOAD?

Some variation between expert and novice problem solving performance has been explained by strain on novices' cognitive resources. This research shows how a self-reported workload measure, the NASA-TLX, can be used to assess task difficulty and serve as an indicator of performance deficiencies. Additionally, by comparing problem solving features and performances to NASA-TLX scores, relationships can be identified that are linked to lower mental workload scores, which can inform instructional interventions to help struggling students overcome cognitive overload.

Three relatively well-structured story problems of varying complexity were analyzed for submissions made by 36 students. Results confirmed that higher probability of success were moderately correlated to lower average task load index scores as well as subscales of temporal demand, performance, effort, and frustration. These results confirm that the NASA-TLX can serve as a potential alternative means of assessing task difficulty with additional benefits of alluding to sources of problem difficulty.

When assessing problem solving features in terms of mental workload measures, it was found that two processes, six errors, and one approach strategy were associated with higher mental workloads while two tasks and two approach strategies were associated with lower mental workload. Twelve performance measures were associated with significant effects on mental workload measures; four were associated with lower mental workload measures with eight associated with higher mental workload. Effects on mental workload must be interpreted with caution as highest levels of performance are associated with mid-level mental workload scores, so extreme high or extreme low mental workload can both be detrimental.

INTRODUCTION

Problem solving skills are critical for engineers as they are tasked with tackling some of the most pressing global challenges (Perry, et al., 2008). Because of the importance of problem solving skills, educators should strive to help students obtain knowledge resources and develop skills required for problem solving success. However, problem solving is a complex activity, modeled as a seven stage process: 1) recognize / identify the problem, 2) define and represent the problem, 3) develop a solution strategy, 4) organize knowledge about the problem, 5) allocate resources for solving the problem, 6) monitor progress toward the goals, and 7) evaluate the solution for accuracy (Pretz, et al., 2003). In practice, there is much variability in how people approach the problem solving process. The stages are not utilized by all problem solvers in all situations, and the problem solver may iterate between stages as s/he responds to feedback, either internal or external (Wilson, et al., 1993). It is possible for students to have proficiency in parts of the problem solving cycle but have limitations on other stages.

Yet, typically, success is measured by outcomes, such as solution accuracy (Drury, 1990), which may not give a true measure of a student skills levels. For example, something as minor as a calculation error caused by accidentally pressing the incorrect number on a calculator can lead to an incorrect solution despite knowing how to complete the problem; and yet, a student can obtain the correct answer by following how someone else completes the problem without knowing how to solve it independently.

In the search for behaviors that promote problem solving proficiency, research has classified variations in performance between expert and novice problem solvers (Chi, et al., 1988) presumably because experts' problem solutions exhibit more successful application of problem solving skills. However, methods used by experts to solve problems are not necessarily transferable to novices due to cognitive requirements necessary to use these strategies (Wang & Chiew, 2010). Low cognitive workload capacity has been linked to the use of inefficient approaches, lacking relevant information necessary to solve the problem, and lacking awareness of performance errors (Wang & Chiew, 2010) while higher cognitive workload capacity is predictive of higher performance and the ability to overcome impasses in problem solving (Hambrick & Engle, 2003). If a student's workload capacity is low, then (s)he may lack enough excess capacity to encode new knowledge thus hindering learning (Sweller, 1988).

Some of the factors that have been shown to contribute to cognitive load include the number of tasks to be performed, the need for accuracy, time pressure, and cognitive capacities of the individual (Proctor & Van Zandt, 2008). Researchers have recommended writing things down as a means of reducing cognitive load during the problem solving process (Woods, et al., 2000). This research investigates the relationships between problem solving features, errors, and strategies evident in students' written work with cognitive (mental) workload of first year engineering students in an effort to identify recommendations that may help students suffering from cognitive overload. In addition, problem solving performance measures along the problem solving cycle were analyzed in terms of cognitive load to evaluate whether certain problem solving processes contribute to cognitive load at a higher rate than others.

Assessing Cognitive (Mental) Workload

Mental workload measures assess how draining the task was on the student's cognitive resources (Drury, 1990). Human factors literature offers several ways of assessing mental workload including primary task, secondary task, psychophysiological, and self-report measures (Wilson & Corlett, 2005). Self-report assessments lend themselves as the most practical measure based on their unobtrusive nature, ease of assessment, and quick data collection. The three most widely used subjective measures of mental workload are 1) the Modified Cooper-Harper scale, 2) Subjective Workload Assessment Technique (SWAT) and 3) NASA-Task Load Index (NASA-TLX). All three assessments are generic, can be applied to any domain, and are not obtrusive to task performance when administered after the task (Stanton, et al., 2005).

The Modified Cooper-Harper Scale assesses difficulty level on a ten-item scale from very easy to impossible based on a classification of the demand level placed on the operator. Accurate assessment requires the operator to carefully read each option and make fine distinctions between ratings of mental effort and ability to thwart errors (Wilson & Corlett, 2005). In addition, it cannot be used to diagnose sources of workload stress (Farmer & Brownson, 2003).

The SWAT is a three item scale that rates time load, mental effort load, and psychological stress load on scales of 1-3. The scales do not easily translate to problem solving tasks because the assessment is geared toward tasks that take extensive time. For example, time load is measured on the three point scale: 1= Often have spare time, 2=Occasionally have spare time, and 3=Almost never have spare time. Additionally, SWAT has been criticized for being insensitive to low mental workloads (Stanton, et al., 2005) and has not been empirically validated (Farmer & Brownson, 2003).

The NASA-TLX consists of six subscales, three measuring demand put on the participant by the task and three measuring stress added by the worker as a result of interacting with the task. The NASA-TLX subscales are scored on a continuous scale from zero to twenty (Hart, 2006; Stanton, et al., 2005). The NASA-TLX has been noted as highly reliable, extensively validated, has a high sensitivity, can be used to diagnose sources of workload and takes 1-2 minutes to complete (Farmer & Brownson, 2003). For these reasons, the NASA-TLX was chosen as the tool for assessing mental workload for this research effort.

METHODS

This research explores relationships between mental workload and problem solving features and performance measures. Tablet PCs were used to capture student problem solving attempts and students completed the NASA-TLX survey immediately following completion of the problem solving tasks.

Technology Used to Capture Problem Solving Processes

Problem solving data was obtained via students' completed in-class exercises using a program called *MuseInk*, developed at Clemson University (Bowman & Benson, 2010; Grigg & Benson, 2011). This software was used in conjunction with tablet computers that were made available to all students during the class period. *MuseInk* files (.mi) keep a running log of the entire problem solution process from beginning to end, including erasures, and can be replayed and coded directly in the application at any point in time on the data file. The software enables the researcher to associate codes to the problem solution at any point, even to erased work.

Solutions were analyzed using a validated coding scheme developed by the research group, which classified the problem solving processes based on relevant events. Cognitive and metacognitive tasks were classified into categories based on a theoretical framework of process activities used during mathematical problem solving (Wong, et al., 2002): knowledge access, knowledge generation and self-management. For codes relating to errors, a structure derived from error detection literature in accounting, was used to classify errors as conceptual and mechanical errors (Owhoso, et al., 2002; Ramsay, 1994) with an added classification of management errors to capture errors in metacognitive processes. Strategy codes were obtained from a subset of strategies that appeared most applicable to story problems from the compilation described in "Thinking and Problem Solving" (Nickerson, 1994).

Engineering Problems under Analysis

Three problems were analyzed which covered the topics of 1) solar power system efficiency, 2) electrical circuits, and 3) hydrostatic pressure. All problems had 1) a constrained context, including pre-defined elements (problem inputs), 2) allowed multiple predictable procedures or algorithms, and 3) had a single correct answer (Jonassen, 2004). All three problems were story problems, in which the student is presented with a narrative that embeds the values needed to obtain a final answer (Jonassen, 2010). The first problem involved a multi-stage solar energy conversion system and required calculation of the efficiency of one stage given input and output values for the other stages (Stephan, et al., 2010). The second problem required students to solve for values of components in a given electrical circuit. This problem, developed by the project team, also contained a Rule-Using/Rule Induction portion (a problem having one correct solution but multiple rules governing the process (Jonassen, 2010)), where students were asked to determine an equivalent circuit based on a set of given constraints. The third problem involved hydrostatic pressure calculations and required students to solve for values within the system, and convert between different unit systems (Stephan, et al., 2010). The instructor's judgment of difficulty of the problems was roughly proportional to the length of the solutions to the problem as shown in Figures 7.1-7.3. The instructor perceived that total pressure problem (Figure 7.3) was the least difficult and the equivalent circuit problem (Figure 7.2) was the most difficult with the solar efficiency problem (Figure 7.1) being of intermediate difficulty.

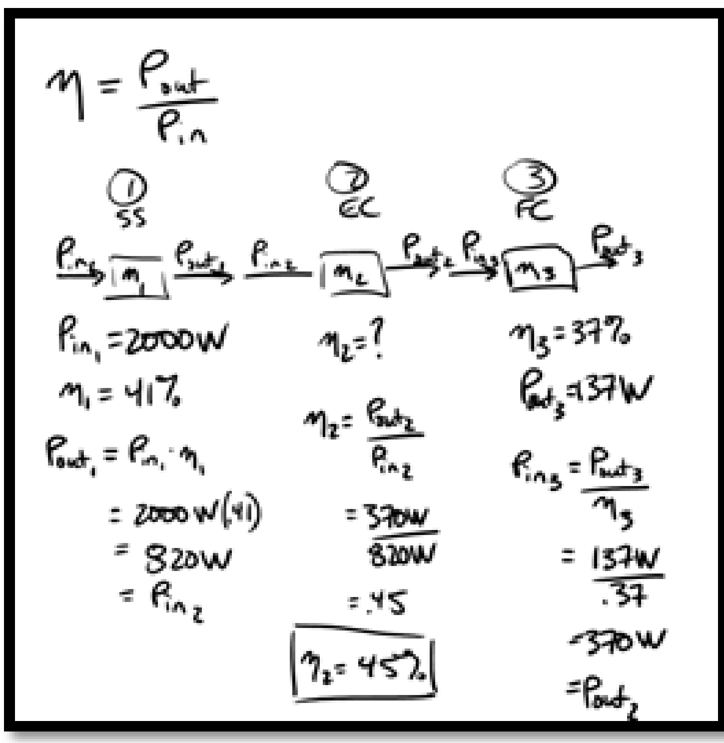


Figure 7.1: Solution for Solar Efficiency Problem

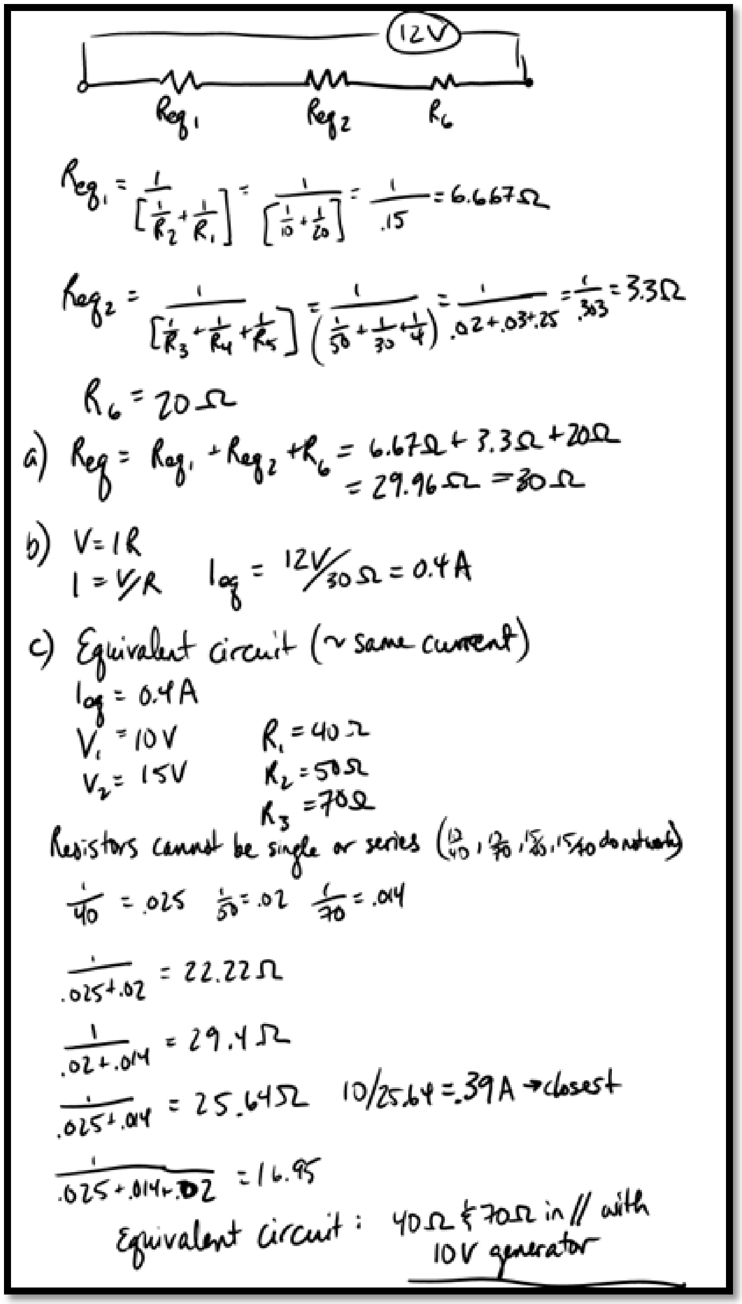


Figure 7.2: Solution for Equivalent Circuits Problem

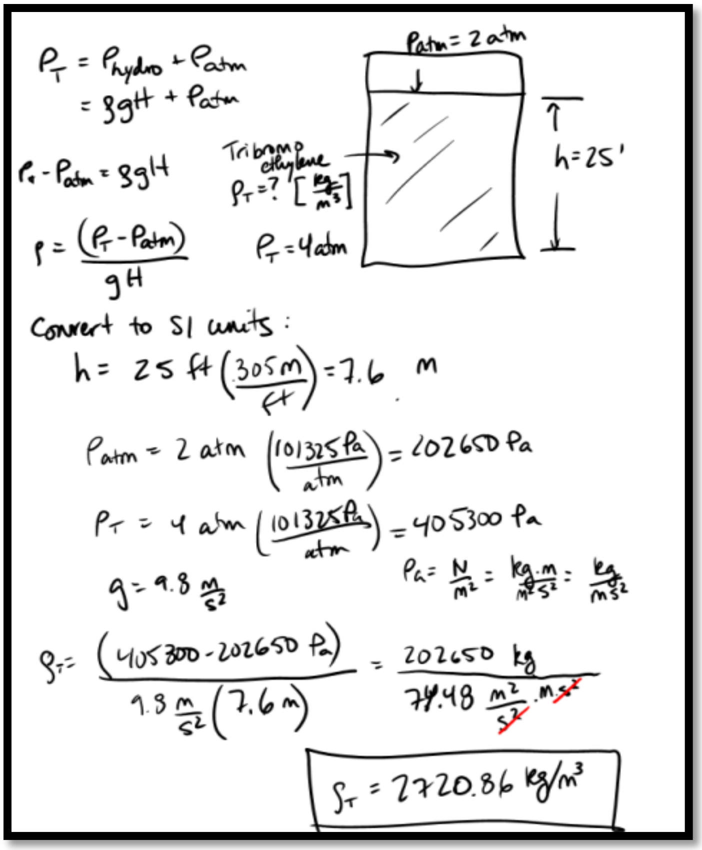


Figure 7.3: Solution for Total Pressure Problem

NASA-TLX survey

The NASA-TLX consists of six subscales, three measuring demand put on the participant by the task and three measuring stress added by the worker as a result of interacting with the task. The three measures of task demand include 1) mental demand, 2) physical demand, and 3) temporal demand. The remaining measures, 4) effort, 5) performance, and 6) frustration, describe the stress put on the person by the interaction of the person with the task (Warm, et al., 2008). Table 7.1 summarizes the survey items.

The NASA-TLX subscales are scored on a continuous scale from zero to twenty. The overall mental workload is calculated by adding together the scores of the individual subscales (Stanton, et al., 2005). For this study, the physical demand subscale was not utilized in calculating the overall mental workload score. The comparison of individual subscale values has become acceptable practice and has been conducted by a variety of researchers in order to evaluate contributors to workload stress (Hart, 2006).

Table 7.1: Items of the NASA-TLX survey (NASA)

Mental Demand	How mentally demanding was the task?
Physical Demand	How physically demanding was the task?
Temporal Demand	How hurried or rushed was the pace of the task?
Performance	How successful were you in accomplishing what you were asked to do?
Effort	How hard did you have to work to accomplish your level of performance?
Frustration	How insecure, discouraged, irritated, stressed, and annoyed were you?

Statistical Analysis

First, to investigate the appropriateness of the NASA-TLX as a measure of problem solving difficulty, the mean mental workload scores were compared to each student's probability of obtaining a correct answer for each problem. Then, Spearman's rho rank correlational coefficients were calculated to assess the level of association between solution accuracy and individual subscales of mental workload. Non-parametric tests were utilized because answer accuracy was not normally distributed for this sample, though measures of mental workload were normally distributed.

Next, the effects of various problem solving features on mental workload were evaluated. Repeated measures analyses were conducted, using a linear mixed-effects model (Seltman, 2012) to assess significant effects of completing a task, making an error, or using a strategy while taking into account extraneous factors such as the problem and the participant. Analyses were conducted on 46 codes of process elements, errors, and strategies, shown in Appendix D.

Finally, the effects of problem solving features were evaluated in terms of differences in mental workload as a secondary measures of their predictive ability (success was assessed in Chapter 6 as the primary measure). Repeated measures analyses were conducted using linear mixed-effects models to evaluate the effect of performance on measures of mental workload and workload subscales while taking into account extraneous factors of the problem and the person. Solutions were evaluated on 28 internal process measures of students' problem solving skills organized according to Sternberg's seven stage problem solving cycle as well as six additional metrics that measure the outcomes in terms of speed and accuracy. Performance measures and their calculations are shown in Appendices E-F.

RESULTS

Comparing solution accuracy with mental workload measures

Average mental workload scores and the probability of success were calculated for each of the three problems. Ideally, average perceived mental workload scores would fall just slightly above 50 to indicate that the problems were challenging yet achievable, though students reported levels slightly below and achieved higher levels of success than expected. As shown in Table 7.2, there is an apparent inverse relationship between mental workload and probability of success; when more students obtained the correct answer, average scores of mental workload were lower. However, all three problems resulted in similar scores for mental workload and for probability of success. Therefore, few definitive conclusions can be drawn from the average scores, except that the three problems appear to be approximately equal in terms of difficulty.

Table 7.2: Summary of mean Mental Workload Scores and success rates

	Solar Efficiency Problem	Equivalent Circuit Problem	Total Pressure Problem
Sample Size	(n=26)	(n=21)	(n=24)
Probability of success	0.88	0.89	0.92
NASA-TLX 5	47.04	43.54	41.91

Next, the relationship between mental workload and level of solution accuracy was assessed for the entire sample of seventy-one solutions. For the overall sample, significant effects were found between solution accuracy and measures of mental workload and all subscales except mental demand. Moderate correlations were found between level of success and ratings of frustration (ρ = - 0.30), performance (ρ = -0.27), effort (ρ = - 0.26), temporal demand (ρ = - 0.26), and overall mental workload score (ρ = -0.24) with higher accuracy levels correlated to lower mental workload scores. A summary of results is shown in Table 7.3.

Table 7.3: Pearson correlation coefficients of the relationships between mental workload scores and the probability of success

	Spearman's rho	P value
NASA-TLX 5	-0.24	0.044
Mental Demand	-0.05	0.706
Temporal Demand	-0.26	0.031
Performance	-0.27	0.021
Effort	-0.26	0.029
Frustration	-0.30	0.011

Exploring relationships between problem solving features and mental workload scores

Repeated measures analyses were conducted using a linear mixed effects model to calculate the effects on mental workload using fixed effects of the problem and the task element/error/strategy under question as well as accounting for random effects attributed to the student. Several of the regression models revealed differences attributable to the problem, indicating that relationships may vary based on the characteristics of the problem. Overall, significant effects were found for four problem solving task elements, seven errors, and three strategies to approaching the problem. Results are summarized in Table 7.4 with extended results of regression models included in Appendix K.

Table 7.4: Summary of effects of problem solving features on Mental Workload

		Overall Mental Workload	Mental Demand	Temporal Demand	Performance	Effort	Frustration
Tasks	Identify equation	↘	↘			↘	
	Plug values in equation	↘	↘			↘	
	Use conversion factor		↗			↗	
	Identify known value	↗	↗	↗		↗	
Errors	Inconsistent units			↘			
	Incorrect unknown value				↗		
	Incorrectly relate variables				↗		
	Misuse governing equation	↗					↗
	Incorrect unit derivation	↗					↗
	Incorrect calculation						↗
	Using incorrectly generated information	↗	↗	↗	↗		↗
Strategies	Plug and Chug						↗
	Means-ends-analysis			↘			
	Chunking					↘	

In general, problem solving tasks had more significant effects on measures of perceived mental demand and effort, errors had more significant effects on perceived frustration and their perceived ability to complete the task (performance), and strategies to approaching the problem had more effects on exerted effort. Using incorrectly generated information had the largest impact on scores of mental workload of all tasks, errors, and strategies analyzed.

Results revealed significant effects on overall mental workload for three problem solving tasks and three errors. When students explicitly identified equations and plugged in values, perceived mental workload were lower. Yet, when students identified known values, their perceptions of mental workload were higher. When students misused governing equations, incorrectly derived units, or used incorrectly generated information perceived mental workload was also higher.

There were significant effects on mental demand for four problem solving tasks and one error. When students explicitly identified equations and plugged in values, perceived mental demand was lower. However, when students explicitly used a conversion factor and explicitly identified known values, perceived mental demand was higher. In addition, using incorrectly generated information was associated with higher perceived mental demand.

There were significant effects on perceived temporal demand for one problem solving task, two errors, and one approach strategy. When students explicitly identified known values or used incorrectly generated information, their perception of temporal demand was higher. When students had inconsistent units, their perception of temporal demand was lower, as was the case when students utilized a means-ends-analysis approach strategy.

There were significant effects on performance strain for three errors. When students incorrectly related variables, had incorrect unknown values, or used incorrectly generated information, their perceptions of performance strain were higher and thus felt less confident that they were able to accomplish the task successfully.

There were significant effects on effort for four problem solving tasks and an approach strategy. When students explicitly identified equations and plugged in values, their levels of perceived effort were lower. However, when students used conversion factors or identified known values, their perceptions of perceived effort were higher. In addition, utilizing a chunking strategy was associated with a lower perceived effort.

Lastly, there were significant effects on perceived frustration for four errors and one approach strategy. When students misused the governing equation, had an incorrect calculation, incorrectly derived units, or used incorrectly generated information, their levels of perceived frustration were higher, as were perceptions of frustration when a plug and chug strategy was utilized.

Identifying performances associated with extreme scores of mental workload

Repeated measures analyses were conducted in order to calculate the significant effects on mental workload using fixed effects of the problem and the performance measure under question while accounting for random effects attributed to the student. A summary of significant effects can be found in Table 7.5 and detailed in Appendix L. Overall, significant effects were found for seven of the twenty-eight internal process measures and five of the six outcome measures. Having a correct representation was the internal process measure with the most impact on mental workload scores while conceptual errors was the outcome measure with the largest association with mental workload scores. In most cases, the specific problem was not a significant factor influencing mental workload, suggesting that these effects are generalizable across problems.

Results revealed significant effects on overall mental workload for three internal process measures and three outcome measures. When students had correct representation and correct equations, their perceived mental workload was lower. Mental workload was higher when more attempts were necessary to correct mechanical errors. In addition, mental workload was higher when conceptual errors were present, with higher error rates, and with attempts that took longer to complete.

Similarly, mental demand was lower when students had correct representations and higher when a conceptual error was present.

Table 7.5: Relationships between performance measures and mental workload

Performance Measures		Overall Mental Workload	Mental Demand	Temporal Demand	Performance	Effort	Frustration
Recognize / identify the problem	# Tries to get correct unknown				↗		
Represent the problem	Explicit visual					↘	
	Correct representation	↘	↘	↘		↘	↘
Organize knowledge about the problem	Correct equation	↘				↘	↘
Allocate resources (Execution)	# Tries to get correct mechanical execution	↗					↗
	Overprocessing				↗		
Monitor progress toward the goals	False alarm rate				↗		
Solution Accuracy	Answer Accuracy				↘		
	Conceptual Errors	↗	↗	↗	↗	↗	↗
	Management Errors			↗	↗		
Solution efficiency	Error Rate	↗		↗	↗		↗
	Time to complete	↗		↗	↗		

Temporal demand was also alleviated by a correct representation and higher with conceptual errors as well as management errors, a higher error rate, and a longer time to complete the problem. Perceived performance strain was related to the most performance measures. Students who took more tries to overcome incorrect unknown values, those who erased correct work more often (and related, those with higher false alarm rates) reported higher performance strain. The same was true for students who committed conceptual errors, management errors, had a higher error rate, and took longer to complete the problem. In addition, students with more accurate solutions reported lower performance strain.

Students who utilized more advanced strategies, had correct representations, and had correct equations, reported perceived effort as lower. Students that committed more conceptual errors reported perceived effort as higher.

Similar results were shown for students in terms of perceived frustration. Students who had correct representations and correct equations reported lower perceived frustration. Students who took more tries to overcome mechanical errors, had more conceptual errors, and had higher error rates reported higher perceived frustration.

Discussion

The mental workload scores indicated the same distribution of problem difficulty across problems as the measure of probability of success; however, the subscale measure of frustration was most highly correlated with problem solving success. It seems appropriate that either overall mental workload or the subscale of frustration can serve as potential alternative means of assessing problem difficulty rather than probability of success. The benefits of using the NASA-TLX as an indicator of problem difficulty is that it can be used to identify students who feel like they are having trouble completing the problem and it reveals whether the struggle was due to time pressure or the problem itself. It can alert instructors to negative affective outcomes such as high frustration that may affect a student's sense of autonomy. On the other hand, if all the instructor wants to know is the difficulty of the problem solving task, then simply asking students to rate how well they were able to accomplish the task (performance) on a scale between failure and perfection or how frustrated they were with the task will likely be sufficient.

The assessment of problem solving features suggests some methods that can keep mental workload at optimal levels. Explicit equation identification and subsequently plugging in values was associated with lower mental workload, which could be used by novice problem solvers as a way of reducing mental workload if capacity is an issue, along with utilizing a means-ends-analysis strategy. However, the interpretation of effects attributed to identifying known values is less clear. Identifying known values was associated with higher perceived mental workload, which can be explained in two ways. Either students with lower mental workload capacity identified known values as a way to reduce mental workload or the process of identifying known values raised metacognitive awareness of how difficult the task truly was.

Errors should always be avoided and generally were correlated with higher mental workload. However, the error of inconsistent units was associated with lower temporal demand, most likely due to the oversimplification of the problem. Similarly, using a conversion factor was found to be associated with higher mental demand and higher effort, though these were likely the result of higher metacognitive awareness of the difficulty of the problem.

Similar effects were found for performance measures. Drawing a correct visual representation and correctly identifying equations are performances associated with lower mental workload and workload subscales, so the development of these skills should be emphasized. In addition, certain inefficient performances were strongly associated with higher mental workload or workload subscales such as requiring multiple attempts before obtaining the correct unknown value and correct mechanical execution, overprocessing and higher false alarm rates (which are both indicators of erasing correct work), making conceptual and management errors, and taking more time to complete the problem. Ideally, these should be avoided if possible, but often occur when mastery has yet to be achieved, and are normal outcomes of the learning process.

CONCLUSIONS

The NASA-TLX is an appropriate gauge of problem difficulty as it yields similar results to other accepted methods, such as the probability of success, while generating much richer information about what students are (or are not) struggling with. Instructors and researchers can utilize a student's self-report NASA-TLX scores as an indicator of cognitive overload by charting student's perceived workload scores; flagging students who report mental workloads larger than one standard deviation above the mean for additional attention. An example is shown in Figure 7.4.

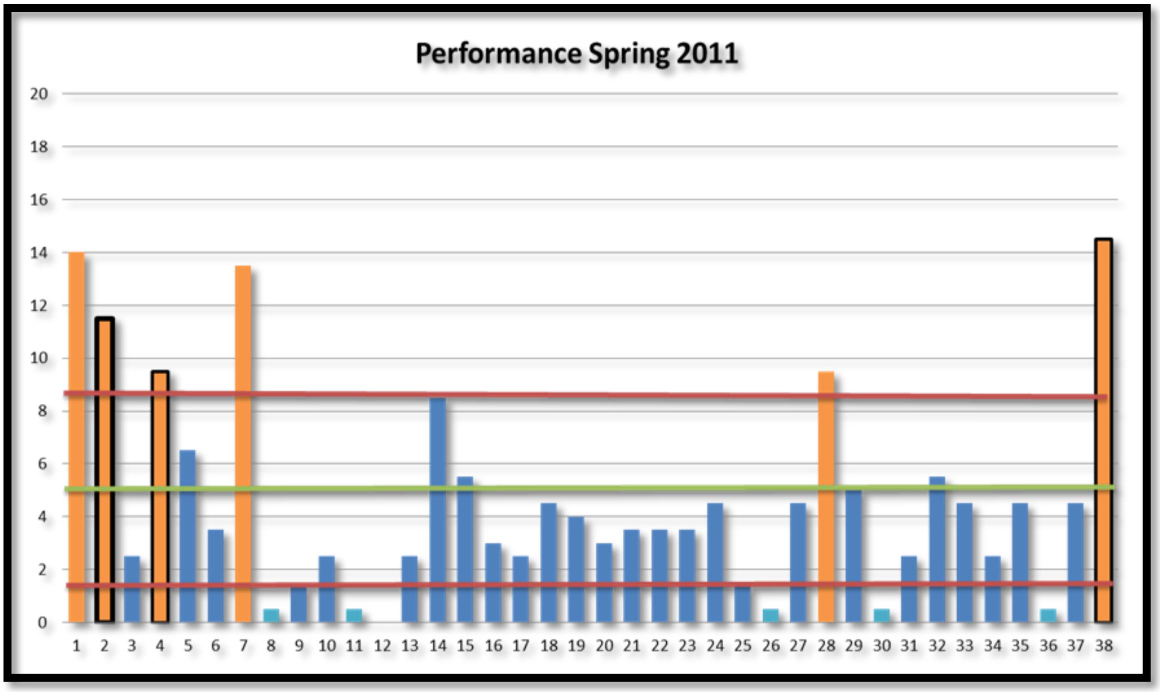


Figure 7.4: Example of plotting perceived performance levels to identify students suffering from overload. The above example suggests students 1,2,4,7, 28, and 38 would be candidates for additional instructor attention.

Based on the results of the study, it is concluded that instructors should encourage students struggling with cognitive overload to explicitly identify relevant equations and draw a representation of the system depicting relationships between variables, as these actions were associated with lower mental workload scores. It is also important to encourage error identification skills, as incorrect identification of errors was associated with higher mental workload. Having students conduct peer assessment activities may be one way of encouraging the development of this skill, so long as students are given feedback on the accuracy of those activities. More research is needed to determine whether the error identification skills of other students work would transfer to the ability to self-assess concurrently with problem solving or whether novice students would be unable to utilize those skills successfully due to other loads on mental workload capacity.

CHAPTER EIGHT

HOW DOES STUDENT ACADEMIC PREPARATION INFLUENCE HOW STUDENTS SOLVE PROBLEM?

A key goal of engineering educators is to identify factors that can limit students' success in engineering. In first year engineering courses, students possess a wide range of academic preparation such as their exposure to various mathematics courses and pre-engineering programs. Additionally, students bring perceptions about their abilities, and have already begun practicing preferred methods of analysis and documentation. Understanding how students with different backgrounds develop problem solving skills in first year engineering programs is of critical importance in order to close achievement gaps between diverse populations.

This study examines how students solve engineering problems and identifies variations based on student factors of gender, ethnicity, prior engineering experience, and mathematics preparation. Solutions for three problems from 27 students were analyzed. Differences in how students solve problems were assessed based on the prevalence (or absence) of elements and errors in the problem solving process, which were evaluated using task analysis.

Results revealed the female students in this study seemed to struggle more than male students with their problem solving attempts; however, this may be confounded by the dramatic difference in prior academic preparation. Few effects were found to be related to the ethnicity of the student. Contrary to initial expectations, pre-engineering experience did not have a significant impact on successfully solving problems; however, there does appear to be an impact on how students solve problems in terms of both style and approach. Yet, having completed a calculus course was significantly related to successful problem solving, and lacking calculus experience was related to an increased number of errors and a longer completion time. Future research will investigate ways of overcoming achievement gaps between populations through focused pedagogical interventions such as through providing feedback on processing errors and inefficiencies.

INTRODUCTION

In view of the one-way migration pattern from engineering majors (Ohland, Sheppard, Lichenstein, Eris, & Charchra, 2008), it is important to identify factors that cause students to withdraw from or fail to succeed in engineering courses. Engineering students from underrepresented populations such as females and minorities have been shown to have distinctly different engineering education experiences (Adelman, 1998). Research indicates that males seem to exhibit more advanced problem solving performances than females (Zhu, 2007) and that females doubt their problem solving abilities more than males (Felder, Felder, & Mauney, 1995). Research on the mathematical problem solving of minority students has shown that they suffer a larger dropout rate from engineering than all other students (National Research Council .

Retention Task Force & National Research Council . Committee on Minorities in Engineering, 1977) and exhibit a lower success rate solving non-routine problems, even though their solutions indicate proportional skills levels (Malloy & Jones, 1998). Non-routine problems were those that could be solved with multiple strategies and required inferential, deductive, or inductive reasoning (Malloy & Jones, 1998). This definition of non-routing problems describes contextual "story" problems typical of those used in the first year engineering course under investigation. If this trend is evident in first year engineering problem solving, it could shed light on a potential factor attributing to the higher than average withdrawal rate for under-represented minorities. Understanding how students with different backgrounds develop problem-solving skills in first year engineering programs is of critical importance in order to close achievement gaps between diverse populations.

Another potential factor is the level of academic preparation. Engineering students must apply basic mathematical skills and reasoning to solve problems, ranging from arithmetic manipulations to analysis of variables. However, the level of mathematic and engineering preparation they bring to their first-year courses vary widely. Often instructors find that students do not have the prerequisite knowledge needed or have strong enough analytical skills to learn new concepts successfully. When students work through problems, they construct an interpretation of the concepts being taught using pre-existing knowledge (Bruner, 1973). For meaningful learning to occur, a learner must make sense out of the information presented and have relevant conceptual knowledge to anchor new ideas (Novak & Gowin, 1984). A learner's framework of relevant concepts allows him or her to solve problems efficiently and successfully. When this prior knowledge is lacking or inappropriate, the learner has difficulty solving the problem in the intended manner (Chi, et al., 1981).

This study investigates the relationship between how students solve problems and their academic experiences prior to taking their first engineering course, specifically their prior mathematics courses and any pre-engineering experience such as involvement in FIRST or Project Lead the Way. FIRST is a program that encourages students ages 6-18 to build science, engineering, and technology skills through designing, building, and programing robots (First, 2010). Research suggests that students who participated in FIRST Lego League experienced increases in confidence and overall technological problem solving performance (Varnad, 2005). Project Lead the Way is a Science, Technology, Engineering, and Mathematics (STEM) education curricular program geared toward middle and high school students. Its goal is to develop critical-reasoning and problem-solving skills (Pltw, 2012). Research suggests that students who participate in Project Lead the Way have higher achievement in reading, mathematics, and science (Bottoms & Anthony, 2005).

METHODS

This research explores relationships between academic preparation and problem solving features and performance measures. Tablet PCs were used to capture student problem solving attempts.

Participants and Problems

This study examines problem solving solutions from 27 students enrolled in a first-year undergraduate engineering course. Three problems were chosen for analysis that covered a range of topics typical of an introductory engineering course including 1) efficiency, 2) circuits, and 3) pressure. All problems 1) had a constrained context, including pre-defined elements (problem inputs), 2) allowed multiple predictable procedures or algorithms, and 3) had a single correct answer (Jonassen, 2004). All three problems were story problems, in which the student is presented with a narrative that embeds the values needed to obtain a final answer (Jonassen, 2010).

Data collection instruments

Students completed a beginning of the semester survey, which asked open ended responses to questions of a) gender, b) ethnicity, c) participation in any pre-engineering activities, and d) previous mathematics courses and grades. There were 21 male and 6 female participants. Twenty-three of the participants were Caucasian. Seven of the students had prior engineering experience through extracurricular activities. Four of the students' highest mathematics course was Pre-Calculus, 3 had taken AP Statistics but no Calculus, 11 had taken AB Calculus, and 9 had taken BC Calculus. Sixty-eight solutions were analyzed in all.

Technology used to Capture Problem Solving Processes

Problem solving data was obtained via students' completed in-class exercises using a program called MuseInk, developed at Clemson University (Bowman & Benson, 2010; Grigg & Benson, 2011). This software was used in conjunction with tablet computers that were made available to all students during the class period. Students worked out problems in the MuseInk application, which digitally records ink strokes and allows researchers to associate codes to the problem solution at any point, even in portions of the work that had been erased. Solutions were coded using the coding scheme developed to describe cognitive and metacognitive processes, errors, and strategies revealed in student work. This coding scheme is included in Appendix D.

Statistical Analysis Methods

Solutions were analyzed using a validated coding scheme developed by the research group, which classified the problem solving processes based on relevant events. For codes related to process elements, the basic structure set forth in the coding scheme of mathematical problem solving was used with categories of knowledge access, knowledge generation, self-management (Wong, et al., 2002). For codes relating to errors, a structure derived from error detection literature in accounting, was used to classify errors as conceptual and mechanical errors (Owhoso, et al., 2002; Ramsay, 1994) with an added classification of management errors to capture errors in metacognitive processes. Strategy codes were obtained from a subset of strategies that appeared most applicable to story problems from the compilation described in "Thinking and Problem Solving" (Nickerson, 1994).

To investigate variations in how students solve problems, statistical analyses were conducted to assess differences between groups in terms of the presence of problem solving elements. Statistical analyses were conducted to investigate whether there were differences in how students solved problems based on participant factors of 1) gender, 2) ethnicity, 3) pre-engineering experience, or 4) calculus experience. Then, statistical analyses were conducted to evaluate whether there were differences in terms of problem solving performance between groups.

Evaluation of the Variations in How Students Solve Problems: As a primary investigation, Chi Square tests were conducted to test whether differences in proportions were larger than due to chance. All problem solving features occurring at least once in the problem solving attempts were classified as occurring, even if the work was later modified to eliminate its presence in the final solution. Then, odds ratios were calculated to determine the magnitude of how much more likely solutions completed by a particular group were to contain a task element, contain an error, or use a strategy. For this analysis, each solution was treated as an independent sample as we were not interested in differences between problems; therefore, these results are only approximations. A secondary analysis was conducted in order to evaluate the predictive value of student factors and the specific problems on the features present in problem solving attempts. Linear mixed-effect models were utilized to evaluate these relationships.

Evaluation of Variations in Performance Measures Based on Participant Factors: Statistical analyses were conducted to evaluate whether there were variations between groups in terms of performance. Twenty-eight internal process measures of students' problem solving methods and skills organized according to Sternberg's seven stage problem solving cycle were evaluated (Pretz, et al., 2003). Five outcome measures were also evaluated. A summary of the performance measures and their calculations is included in Appendix E. Chi Squared tests were conducted to directly compare differences in performance measures of categorical nature and Wilcoxon sum rank tests were conducted on performance measures that were of interval or ratio data types, using the Chi Squared approximation to determine the level of significance. Then, linear mixed-effects models were utilized to assess the predictive strength of participant factors and the problems on performance measures.

RESULTS

Assessment of problem solving variations by Gender

The level of academic preparation of female students was quite different from that of male students. Males were more likely to have both pre-engineering experience ($p=0.0004$) and calculus experience ($p=0.0001$). Of the female students in the study, only 33% had calculus experience compared to 86% of male students. Additionally, none of the female students had pre-engineering experience compared to 33% of male students. Therefore, it should be noted that differences found in terms of gender are likely due (at least in part) to differences in level of academic preparation.

Chi squared tests and odds ratios indicated that females were more likely than males to explicitly write out equations and then plug in values in separate steps ($p = 0.042$), and had a higher occurrence of incorrectly deriving units ($p=0.002$). Additionally, females' solutions were more likely to indicate the use of lower level strategies such as a "guess and check strategy". Results are summarized in Table 8.1 and the complete assessment of odds ratios is in Appendix M.

In terms of performance assessment, males tended to use higher-level strategies than females ($p=0.005$), correctly identify known values ($p=0.039$), have a lower false alarm rate (do not erase correct work as often) ($p=0.050$), and obtained a higher proportion of accurate final answers ($p=0.002$). A summary is shown in Table 8.2.

Table 8.1: Significant effects of gender based on Chi Squared tests and odds ratios

Process Analysis Measure	**Chi Square**	**p value**	**Mean (Male)**	**Mean (Female)**	**Odds Ratio (Male more)**	**Odds Ratio (Female more)**
Plugged values in equation	4.13	0.042	0.77	1.00	0.1	9.3
Incorrect unit derivation	4.52	0.034	0.04	0.20	0.2	6.4
Guess and check	4.18	0.041	0.11	0.33	0.3	3.8

Table 8.2: Performance assessment by gender

Process Analysis Measure	**Chi Square**	**p value**	**Mean (Male)**	**Mean (Female)**
Approach Strategy Used	14.36	0.001	0.51	0.20
Number of corrections of mechanical tasks	4.07	0.044	0.08	0.27
Irrelevant information	7.30	0.026	0.17	0.40
Answer Accuracy	11.36	0.001	0.56	0.14

Assessment of Problem Solving Variations by Ethnicity

The level of academic preparation of minority students was roughly equivalent to that of the remainder of the students. No significant differences were found in terms of calculus experience (p=0.338) or pre-engineering experience (p=0.999). Of the minority students in the study, 75% had calculus experience compared to 78% of non-minority students. Additionally, 25% of minority students had pre-engineering experience compared to 26% of non-minority students. Therefore, it is reasonable to assume that differences found based on ethnicity are not attributable to prior academic experiences of participating in a pre-engineering program or completing a calculus class. However, only a few differences were found that were attributed to ethnicity.

The only significant difference found in terms of problem solving features based on ethnicity was a larger number of solutions with correct answers but with incorrect units (p=0.003), as shown in Table 8.3. A complete evaluation of odds ratios is shown in Appendix N.

Table 8.3: Significant effects of ethnicity based on Chi Squared tests and odds ratios

Process Analysis Measure	**Chi Square**	**p value**	**Mean (Caucasians)**	**Mean (Minorities)**	**Odds Ratios (Caucasians more)**	**Odds Ratios (Minorities more)**
Missing Units Throughout	11.95	0.001	0.00	0.20	0.02	45.00

Variation in performances based on ethnicity indicated that the Caucasian students correctly identified known values more often (p=0.01) and completed the problems more quickly (p=0.001) as shown in Table 8.4.

Table 8.4: Performance assessment by ethnicity

Process Analysis Measure	**Chi Square**	**p value**	**Mean (Caucasian)**	**Mean (Minority)**
Correct known values	6.76	0.01	0.98	0.80
Time to completion	6.57	0.01	14.18	23.69

Assessment of Problem Solving Variations by Pre-engineering Experience

In terms of prior academic preparation, few significant findings support claims from the literature that pre-engineering programs enhance problem solving performance. Significant differences were mainly based on format of solving problems; students that had pre-engineering experience had a larger number of solutions where they documented algebraic steps (p=0.019) and explicitly identified their final answers either by boxing in their answer or writing out the conclusion in sentence form (p=0.036). A summary of findings is shown in Tables 8.5 and a comprehensive assessment of odds ratios is shown in Appendix O.

There were no significant differences found for accuracy of solutions. In fact, students with pre-engineering experience were more likely to have errors in their problem definition. A summary of findings are shown in Tables 8.6.

Table 8.5: Effects of pre-engineering experience - Chi Squared tests and odds ratios

Process Analysis Measure	Chi Square	p value	Mean (With Pre-engineering experience)	Mean (Without Pre-engineering experience)	Odds Ratio (With more)	Odds Ratio (Without more)
Document math	5.48	0.019	0.94	0.65	8.73	0.11
Identify final answer	4.39	0.036	0.88	0.61	4.84	0.21

Table 8.6: Performance assessment by pre-engineering experience

Process Analysis Measure	Chi Square	p value	Mean (With pre-engineering experience)	Mean (Without pre-engineering experience)
Correct definition	6.09	0.014	0.76	0.96
Indicate Answer	4.39	0.036	0.88	0.61

Assessment of Problem Solving Variations by Calculus Experience

An extensive set of differences was revealed based on mathematics preparation in terms of calculus experience, with implications on solution accuracy. Students who had taken a calculus class had fewer errors in their solutions. Solutions from students without calculus experience were more likely to solve intermediate values (p=0.048), utilize labeling or renaming (p = 0.005), use incorrectly generated equations (p =0.048), and have missing units throughout the entire attempt (p = 0.013). Results are shown in Tables 8.7 and a complete analysis of odds ratios is included in Appendix P.

Table 8.7: Effects of calculus experience based on Chi Squared tests and odds ratios

Process Analysis Measure	Chi Square	p value	Mean (With Calculus Experience)	Mean (Without Calculus Experience)	Odds Ratio (With more)	Odds Ratio (Without more)
Solve Intermediate value	3.91	0.048	0.80	1.00	0.11	8.86
Labeling / Renaming	7.87	0.005	0.38	0.76	0.18	5.46
Using incorrectly generated information	3.92	0.048	0.18	0.41	0.31	3.27
Missing units throughout	6.18	0.013	0.00	0.13	0.06	16.61

Students without calculus experience also suffered more conceptual errors ($p=0.032$) and mechanical errors ($p=0.015$) as well as took longer to complete problems ($p=0.002$). Results are shown in Table 8.8.

Table 8.8: Performance assessment by calculus experience

Process Analysis Measure	Chi Square	p value	Mean (With Calculus Experience)	Mean (No Calculus Experience)
Conceptual Errors	4.59	0.032	0.33	0.71
Management errors	5.96	0.015	1.06	2.06
Time to completion	9.53	0.002	14.05	20.17

Comparison of Problem Solving Features Using Linear Mixed-Effects Models

A linear mixed-effects model was used to fit a model that took into account all participant factors simultaneously to determine whether the combination of participant factors influenced the significance of findings. The participant was set as a random factor with fixed effects of the problem, gender, ethnicity, pre-engineering experience, and calculus experience. Eight significant effects were found in terms of problem solving features and seven significant effects in terms of performance.

In terms of problem solving features, there was a heavy influence on significant effects based on the problem, and as a results, there was much variability in the results from the linear mixed model over Chi squared tests. Two relationships were reinforced;

those having pre-engineering experience were more likely to identify the final answer and female students were more likely than males to have incorrect unit derivations. However, incorrect unit derivations were also associated with being a minority student, having calculus experience, and lacking pre-engineering experience. Five new but related effects revealed that those with calculus experience were more likely to explicitly manipulating equations to solve for variables before plugging in values, students with pre-engineering experience were more likely to ignore problem constraints, and females and those with pre-engineering experience were more likely to solve for the wrong unknown value. In addition, females showed a higher use of the plug-and-chug strategy while Males who were Caucasian and did not have calculus experience were more likely to use means-ends-analysis. Results can be found in Appendix Q.

In terms of performance, significant effects were reinforced for six of the eleven performance measures; however, none of the significant effects associated with calculus experience remained significant after assessing all participant factors jointly. Females, Caucasians, and those with pre-engineering experience were more likely to utilize explicit definition tasks, though students with pre-engineering experience were also more likely to have incorrect definition tasks (derived from the high occurrence of ignoring problem constraints). This assessment also reinforced that males used higher-level strategies to approach the problem, males had higher answer accuracy, those with pre-engineering experience were more likely to identify the final answer, and minority students took longer to complete the problems. Correctly identifying known values was related to all participant factors, with males, Caucasians, those with calculus experience and those without pre-engineering experience obtaining correct known values more often. Results can be found in Appendix R.

DISCUSSION

This analysis revealed several significant differences in how different students from this class solved problems. It is important to point out that the findings from this study many not be generalizable to all classes or even all sections of the particular course that was investigated. However, other instructors could utilize the methodology described in this paper as a means of identifying the areas of instructional needs of students in their own classes. The important thing to take away from this research is that participant factors do have a profound impact on how students solve problems when they are allowed to solve problems based on their preferred method, as was the case in this investigation. It is important to get an initial gauge of student skills so that instruction can be tailored as appropriate.

That being said, the findings from this investigation do reinforce some of the findings in past literature on gender and ethnicity differences. This investigation found evidence of females using lower level strategies (guess-and-check and plug-and-chug) more often than males. Also, there were few discernible differences in problem solving abilities based on ethnicity. This investigation did not show a difference based on solution accuracy but there was a significant difference in time to complete the problem, which could affect success rate if there is a time constraint.

In addition, results from this investigation indicated that problem solving techniques can be taught, as evidence of more formal problem solving techniques was evident in work completed by those with pre-engineering experience that were likely developed in those programs such as documenting math and indicating the final answer. However, the speed and accuracy of problem solutions were not impacted by pre-engineering experience. The only negative item associated with pre-engineering experience was the error of ignoring problem constraints, which in turn reduced the accuracy of the problem definition. All instances occurred in the second problem, the equivalent circuit problem. The students may have adopted a slight overconfidence based on their prior experience and jumped into solving the problem without fully understanding the constraints of the problem, or it could simply be a fluke. However, it would be interesting to see if the effect would disappear if the problem was presented in a more hands-on approach where students were actually given the physical components available for use in the equivalent circuit.

As predicted, prior math experience was highly correlated with measures of problem solving success, with evidence of solutions with fewer conceptual and management errors and faster completion times based on higher levels of mathematics preparation. Calculus experience was also associated with techniques that are more efficient such as avoiding tasks such as solving for intermediate values or renaming variables. However, these effects were washed out when all participant factors were evaluated jointly. It is unlikely that having experienced a calculus class directly affects these outcomes, as calculus was not needed to solve any of these problems. It is more likely that the student's advanced abilities have afforded them the opportunity to complete a calculus class before entering this class or that practice solving problems from a higher difficulty math course has helped them develop stronger problem solving skills.

CONCLUSIONS

While the problem solving techniques and resulting performances vary greatly across incoming students, there is no reason for instructors to remain blind to these differences. By conducting a performance assessment, instructors can uncover deficiencies held by individual students or assess the overall skill level of the class in order to set reasonable expectations. If this evaluation had been conducted at the beginning of the semester, instructors would have been able to recognize the risk held by the female students. The instructor could have possibly provided additional guidance to help them develop skills necessary to achieve problem solving success at a higher rate than 1/15 as was the case in this assessment.

Results also reveal the importance of knowing that students have the pre-requisite knowledge required to succeed in the course. It may have been helpful to provide additional assistance to students who did not have calculus experience before taking the course. A different option would be to group students into peer teams where they can work together to solve problems, distributing students based on pre-engineering experience and prior math experience to ensure a diverse team. The number of potential interventions based on the skills and abilities of students is nearly endless. However, the purpose of this study is not to postulate on what interventions may be best, but to provide a framework that will provide means of evaluating potential achievement gaps between populations. This method may be used by future research to assess the effectiveness of instructional interventions in reducing achievement gaps.

CHAPTER NINE

ENHANCING PROBLEM SOLVING ASSESSMENT WITH PROCESS CENTERED ANALYSIS

In order to assess the development of skills, it is necessary to be able to assess the students' individual performances on a common set of criteria at various points in their studies. Traditional approaches to grading problem solving solutions only enable the evaluation of solution accuracy and do not give insight into students' problem solving skills levels. The purpose of this research is to establish an evidenced-based method for assessing problem solutions that can be utilized by researchers and instructors to assess problems from a variety of contexts using a common assessment.

Performance measures were assessed by evaluating the level of association between internal process measures and outcome measures using linear mixed-effects models. This assessment was then used to create two rubrics that can be utilized to assess student skills levels throughout the problem solving process that are linked to problem solving success: one for use with recorded solutions and one for use with paper solutions. While this rubric is based on evaluations of performance from well-defined story problems, it is projected that these rubrics can also be applied to a wider range of problem solving tasks.

INTRODUCTION

Traditionally, student problem solving performance is assessed based on outcomes but ultimately the grading criteria is up to the instructor's judgment, and everyone has their own opinion (Reeves, 2008). Therefore, grading policies do not always accurately represent a student's level of achievement or learning gains. The most effective grading policies provide accurate, specific, and timely feedback designed to improve student performance and assign grades based on summative assessment, taking into account the trend of student achievement across the semester rather than averaging performances (Marzano & Heflebower, 2011; O'Connor, 2010).

Standards-based assessment is gaining popularity as a means of assessing that a student has achieved minimum competencies. In this system, students are compared to benchmarks for what they are expected to know rather than comparing to a norm such as the class average. Standards based assessments rely heavily on rubrics or scoring guides to encourage consistency in assessment across performance evaluations (Reeves, 2002). Effective rubrics 1) include all important elements, 2) include only unidimensional elements, 3) have ratings that are distinct, comprehensive, and descriptive, and 4) communicates clearly with learners (Jonassen, 2004). Jonassen suggests a six item rubric of criteria to evaluate performance of story (word) problems: 1) accuracy of problem classification, 2) identification of initial conditions, 3) accuracy of equations, 4) accuracy of answer estimate, 5) unit consistency, and 6) accuracy of answer (Jonassen, 2004). He suggests grading on a continuum from Inadequate to Adequate to Exceptional. While this seems like a great means of standards-based assessment of problem solving (for solving story problems), it fails to meet the first objective of effective rubrics, include all important elements. As Table 9.1 illustrates, the rubric suggested by Jonassen only evaluates performance on four of the seven steps of the problem solving cycle (Pretz, et al., 2003).

Table 9.1: Problem Solving Processes and Outcome Measures

and the Ability to Assess them with Rubrics

Problem Solving Process (Pretz, Naples, et al.)	**Rubric Assessment (Jonassen)**
1) Recognize / identify the problem	1) Accuracy of problem classification 2) Identification of initial conditions
2a) Define the problem	Not assessed
2b) Represent the problem	Not assessed
3) Develop a solution strategy	Not assessed
4) Allocation of resources to solve the problem (execution)	5) Unit consistency
5) Organize knowledge about the problem	2) Identification of initial conditions 3) Accuracy of equations
6) Monitor progress toward the goals	Not assessed
7) Evaluate the solution	4) Accuracy of answer estimate
Outcome Measures	6) Accuracy of answer

Filling-in the Assessment Gaps

It is important to be able to assess variations across all problem solving processes and the resulting impact on problem solving assessment for research purposes to inform instructional interventions that could improve awareness of skills deficiencies. If the only way to assess problem solving attempts was using retrospective analysis of handwritten paper solutions, a rubric containing assessment of the six items provided by Jonassen may be the best means of assessment available within the constraints of the medium. However, when a recording of the entire problems solving process is available for analysis, as through video recordings or digital Ink (as used in this research effort), then process analysis can be used to evaluate additional problem solving skills. Process-based analysis examines methods and systems and looks to identify weak points in the process (Scheer, 2003) and can also be used to assess efficiency of processes. While this form of assessment is more labor intensive, the enhanced assessment can uncover skills deficiencies and has the potential for significant improvement in student learning gains.

MEASURES OF INTERNAL PROCESSES OF THE PROBLEM SOLVING STAGES

Education and human performance literature was utilized to determine measures that evaluate student performance within the seven stages of Sternberg's problem solving cycle. Twenty-eight internal process measures were created and used to evaluate student problem solving attempts. Table 9.2 describes the breakout of the number of measures across stages. A list of measures is included in Appendix E.

Table 9.2: Number of measures developed to assess problem solving processes

Problem Solving Stage		Number of measures
1	Recognize / identify the problem	3
2a 2b	Define the problem Represent the problem	3 3
3	Develop a solution strategy	1
4	Organize knowledge about the problem	5
5	Allocate resources for solving the problem	8
6	Monitor progress toward the goals	3
7	Evaluate the solution	2

MEASURES OF PERFORMANCE OUTCOMES

Traditionally, instructors simply evaluate students' solutions based on the accuracy of the final answer (Szetela, 1987). However, other measures can be used to further evaluate the solution in terms of solution accuracy as well as process efficiency. Seven outcome measures were created and used to evaluate the resulting outcomes of student problem solving attempts. Table 9.3 describes the breakout of the outcome measures. Solution accuracy was assessed based on measures of success (100% correct solution), level of accuracy (average level of accuracy, taking into account partial credit for having correct answers with incorrect units and multi-part problems with incorrect answers for some parts), and three measures of different types of errors. Attempt efficiency was assessed based on error rate and time to completion.

Table 9.3: Number of measures developed to assess problem solving outcomes

Problem Solving Stage		Number of outcome measures
1	Solution accuracy	5
2	Attempt efficiency	2

COMPARING PERFORMANCE MEASURES

The level of association between process and outcome measures was evaluated using linear mixed effects models that took into account variations based on the problem, the semester, and random effects of the person. Twenty-two process measures were associated to at least one outcome measure to a statistically significant level. Significant relationships are shown in Table 9.4. Measures of the accuracy of process stages were most highly associated with outcome measures of solution accuracy. Correct definitions, representations, equations, mechanical execution, and management of execution tasks as well as higher level strategies, and error identification skills were related to solution accuracy measures. Measures of the efficiency of process stages were most highly associated with outcome measures of attempt efficiency. Ten measures had significantly significant associations with error rate and ten had significant associations to completion time. In general, the number of corrections made to achieve accuracy for the problem solving stage was associated with higher error rates and longer completion times. Higher level strategies, correct equations, and error identification skills were associated with lower error rates and correct problem definition was related with faster completion times.

Table 9.4: Associations between process measures and outcome measures

Performance Measures		**Success**	Answer Accuracy	Conceptual Errors	Mechanical Errors	Management Errors	Error Rate	Time to complete
Recognize / identify the problem	1B Correct unknown							↗
Define the problem	2B Correct definition					↘		↘
Represent the problem	2D Explicit visual							↗
	2E Correct representation	↗	↗	↘	□	□	□	□
	2F Number of Corrections to representation						↗	↗
Develop a solution strategy	3 Strategy	↗	↗	□	□	↘	↘	
Organize knowledge about the problem	4A Explicit info	□	□	□	□	□	□	↗
	4B Correct known values	↗	□	↘	□	↘	□	□
	4C Correct equation			↘			↘	
	4D Number of Corrections to known values	↗	↗	□	□	□	□	□
Allocate resources (Execution)	5A Execute task			□		↗	□	↗
	5B Correct mechanical	↗	↗	□	↘		↘	□
	5C Number of Corrections Mechanical						↗	
	5D Correct management	↗	□	□	□	↘	↘	□
	5E Number of Corrections Management						↗	↗
	5F Number of tasks					↗	□	↗
	5G Erasing correct work					↗		↗
	5H Irrelevant Info					□	↗	□
Monitor progress toward the goals	6A Sensitivity	↗	↗	↘	□	↘	↘	□
	6B Hit Rate	↗	↗	↘	↘	↘	↘	□
	6C False Alarm Rate					↗		↗

Detailed descriptions of linear mixed-effects models can be seen in Appendix S. Measures from Stage 1: Recognize / Identify the problem did not have significant effects on problem solving success; however, it is likely this is due to the problems being well-defined and including specifically what to solve for. It is projected that in problems that are more ill-defined, measures of this stage would have been more highly associated with outcome measures. There were also no significant effects found for Stage 7: Evaluate the solution, though the sample of students explicitly completing these tasks on their own was so small that the effects could not be evaluated from this sample of solutions. Therefore, it is suggested to retain these measures in the proposed rubric and to be reassessed by future research efforts.

CREATION OF A PROBLEM SOLVING PROCESS RUBRIC

Based on the results of the analysis, an evidence-based rubric was created to assess performance, adjusting scales so that they are summative to problem solving success. The complete rubric of all process measures can be found in Appendix U. The use of this rubric has implication for both research and instructional purposes. This rubric will allow researchers to investigate the effectiveness of various pedagogical interventions in terms of improving problem solving performance and pinpoint the process that was most impacted. It also enables instructors to identify skills deficiencies in students' work and target instructional interventions more effectively.

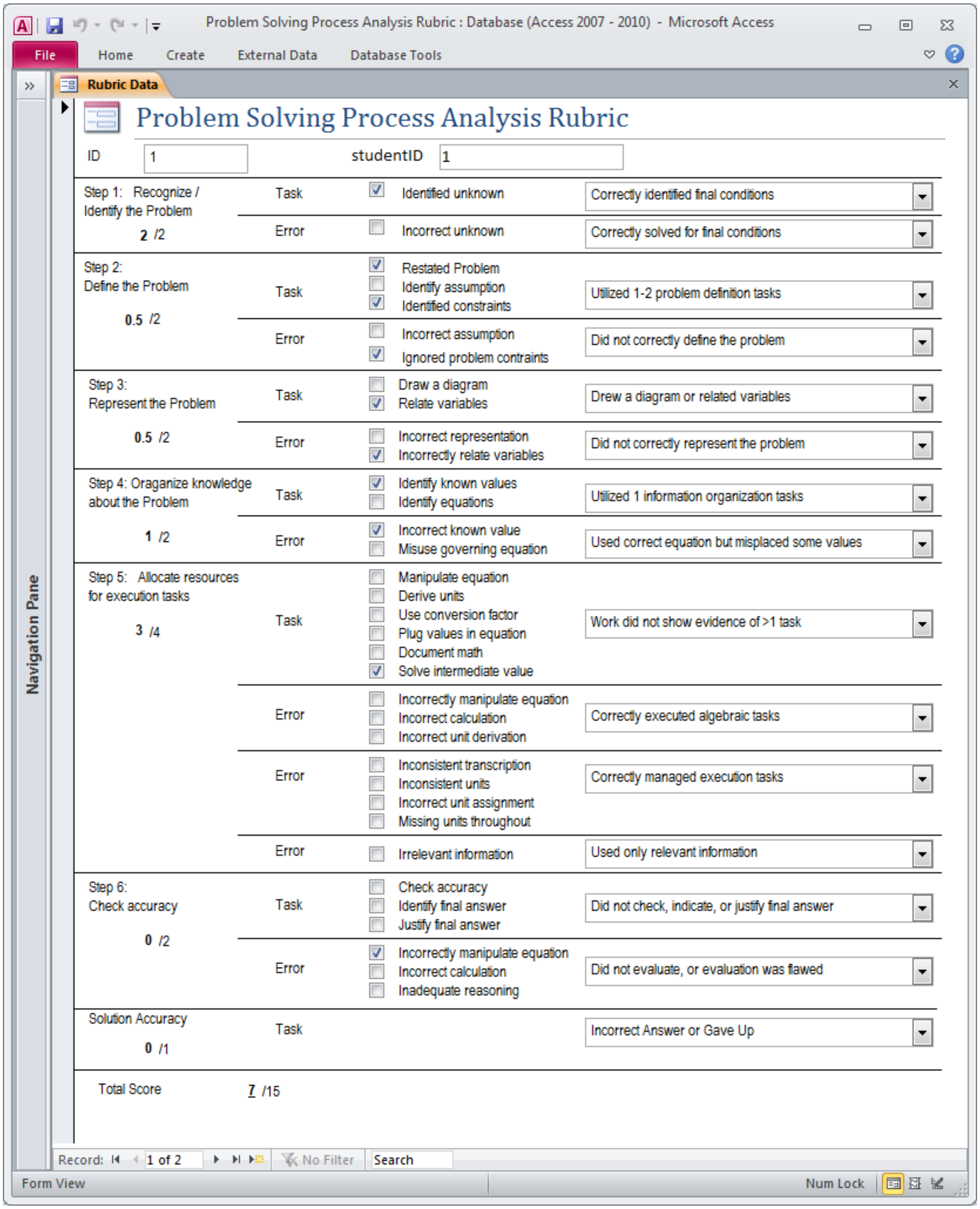
The major advantage to this rubric over traditional grading methods is that it can be utilized as a personalized feedback system to inform students of their level of proficiency as well as pinpoint deficiencies. This information could then be utilized by instructors to route students to resources for overcoming these problems or other instructional interventions.

One difficulty with using the extended process analysis rubric is that recordings of the problem solutions are required for complete use. If researchers or instructors do not have access to a program such as MuseInk, they can still utilize an abbreviated version of the process analysis, but efficiency measures cannot be assessed and process stages 3 and 6, developing a solution strategy and monitoring progress, cannot be adequately assessed without a recorded solution. However, it is possible to utilize a similar rubric for hand written problems that evaluate the problem solution in terms of five of the seven problem solving processes (six of the eight with define and represent the problem are viewed as separate stages) and solution accuracy. The paper version of this abbreviated rubric is shown in Table 9.5 and a screenshot of the database version is shown in Table 9.6. This version of the rubric is more practical for use by instructors or researchers who do not have access to problem recording resources. One challenge that comes from this restricted assessment is how to increase awareness of the two problem solving processes that cannot be evaluated, developing a solution strategy and monitoring progress, as performance in these processes were among the most highly correlated with success.

Table 9.5 Abbreviated Problem Solving Process Analysis Rubric (Paper version)

		Measure	Notes	Inadequate	Adequate	Exceptional	
Identify the problem	Task	Explicit unknown value	☐ Identified unknown	Did not identify final conditions	Incomplete identification of final conditions	Fully identified final conditions	
	Error	Correct Unknown value	☐ Incorrect unknown	Did not solve for correct final condition		Correctly solved for final conditions	
Define the problem	Task	Explicit definition	☐ Restated problem ☐ Identify assumption ☐ Identified constraints	Did not explicitly define the problem	Utilized 1-2 problem definition tasks	Utilized all 3 problem definition tasks	
	Error	Correct definition	☐ Incorrect assumption ☐ Ignored problem constraints	Did not correctly define the problem		Correctly defined the problem	
Represent the problem	Task	Explicit visual	☐ Draw a Diagram ☐ Relate variables	No diagram drawn, no relationships indicated	Drew a diagram or related variables	Diagram drawn with variable relationships indicated	
	Error	Correct representation	☐ Incorrect representation ☐ Incorrectly relate variables	Did not correctly represent the problem		Correctly represented the problem	
Organize knowledge	Task	Explicit knowns and Equations	☐ Identify known values ☐ Identify equation	Did not organize problem information	Utilized 1 information organization tasks	Utilized both information organization tasks	
	Error	Correct knowledge organization	☐ Incorrect known values ☐ Misuse governing equation	Used wrong equation or misplaced several values	Used correct equation but misplaced some values	Equation set up correctly with correct values in correct places	
Allocate resources (Execution)	Task	Execute tasks to arrive at solutions	☐ Manipulate equation ☐ Derive units ☐ Use conversion factor ☐ Plug values in equation ☐ Document math ☐ Solve intermediate value	Work did not show evidence of >1 task	Work showed evidence of 2-3 tasks	Work showed evidence of >3 tasks	
	Error	Correct Execution of tasks (Mechanical)	☐ Incorrectly manipulate equation ☐ Incorrect calculation ☐ Incorrect unit derivation	Did not correctly execute algebraic tasks		Correctly executed algebraic tasks	
	Error	Correct Execution of tasks (Management)	☐ Inconsistent transcription ☐ Inconsistent units ☐ Incorrect unit assignment ☐ Missing units throughout	Did not correctly manage the execution of algebraic tasks		Correctly managed the execution of algebraic tasks	
	Error	Over-production	☐ Irrelevant Information	Used irrelevant information		Used only relevant information	
Evaluate the solution	Task	Check accuracy	☐ Checked accuracy ☐ Indicated final answer ☐ Justify final answer	Did not check, indicate, or justify final answer	Checked, indicated, or justified final answer	Checked, indicated, and justified final answer	
	Error	Correct evaluation	☐ Incorrectly manipulate equation ☐ Incorrect calculation ☐ Incorrect unit derivation ☐ Inadequate reasoning	Did not evaluate, or evaluation was flawed	Evaluation was incomplete	Properly evaluated answer	
Solution		Answer Accuracy		Incorrect Answer or Gave Up	Correct Answer but Missing / Incorrect Units	Correct Answer	
						Score	/15

Table 9.6 Abbreviated Problem Solving Process Analysis Rubric (Database version)



Problem Solving Process Analysis Rubric : Database (Access 2007 - 2010) - Microsoft Access

File | Home | Create | External Data | Database Tools

Rubric Data

Problem Solving Process Analysis Rubric

ID: 1   studentID: 1

Step	Score	Type	Items	Rating
Step 1: Recognize / Identify the Problem	2 /2	Task	[x] Identified unknown	Correctly identified final conditions
		Error	[ ] Incorrect unknown	Correctly solved for final conditions
Step 2: Define the Problem	0.5 /2	Task	[x] Restated Problem [ ] Identify assumption [x] Identified constraints	Utilized 1-2 problem definition tasks
		Error	[ ] Incorrect assumption [x] Ignored problem contraints	Did not correctly define the problem
Step 3: Represent the Problem	0.5 /2	Task	[ ] Draw a diagram [x] Relate variables	Drew a diagram or related variables
		Error	[ ] Incorrect representation [x] Incorrectly relate variables	Did not correctly represent the problem
Step 4: Oraganize knowledge about the Problem	1 /2	Task	[x] Identify known values [ ] Identify equations	Utilized 1 information organization tasks
		Error	[x] Incorrect known value [ ] Misuse governing equation	Used correct equation but misplaced some values
Step 5: Allocate resources for execution tasks	3 /4	Task	[ ] Manipulate equation [ ] Derive units [ ] Use conversion factor [ ] Plug values in equation [ ] Document math [x] Solve intermediate value	Work did not show evidence of >1 task
		Error	[ ] Incorrectly manipulate equation [ ] Incorrect calculation [ ] Incorrect unit derivation	Correctly executed algebraic tasks
		Error	[ ] Inconsistent transcription [ ] Inconsistent units [ ] Incorrect unit assignment [ ] Missing units throughout	Correctly managed execution tasks
		Error	[ ] Irrelevant information	Used only relevant information
Step 6: Check accuracy	0 /2	Task	[ ] Check accuracy [ ] Identify final answer [ ] Justify final answer	Did not check, indicate, or justify final answer
		Error	[x] Incorrectly manipulate equation [ ] Incorrect calculation [ ] Inadequate reasoning	Did not evaluate, or evaluation was flawed
Solution Accuracy	0 /1	Task		Incorrect Answer or Gave Up

Total Score 7 /15

Record: 1 of 2 | No Filter | Search

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IMPLICATIONS FOR PRACTICE

This research investigation revealed several opportunities to advance educational practice in order to promote the growth of strong problem solvers. While the results have only been evaluated in the first year engineering classroom, the techniques are likely extendable to other related areas such as science, technology, or mathematics courses and even non-stem courses and could likely be included in secondary education classes.

Evidence suggests that instructors can promote positive outcomes by encouraging students to utilize planning and visualization tasks, specifically encouraging students to spend time explicitly documenting and checking the accuracy of 1) the unknown value, 2) the known values, 3) the relevant equations, and 4) a schematic visualization of the system (a diagram illustrating the relationships between variables). However, simply requiring the use of these activities is not completely effective, and students may not fully adopt the behaviors as intended unless they understand how they benefit from their use.

The research also provided methods that can be utilized by instructors to identify students who could benefit from personalized instruction. One is to have students self-rate their perceived level of difficulty as with the NASA-TLX survey and identify students that express extremely high ratings of mental workload. A second is to utilize the abbreviated rubric to evaluate the problem solving process and identify students with multiple scores that fall in the inadequate range or an overall score that is low (such as 0 -5 on a 15 point scale).

IMPLICATIONS FOR FUTURE RESEARCH

The results from this research suggested several potential instructional interventions that could potentially be used to aid din the development of problem solving skills. Evaluating the effectiveness of these instructional techniques will be the focus of future research initiatives. Using the extended rubric, researchers can evaluate the variation of performances of specific problem solving processes, comparing student problem solving attempts from the intervention group and a control group where no intervention was implemented.

One currently ongoing research effort is looking at evaluating the effectiveness of implicitly training the problem solving process using guided solutions. Two types of problems were created based on the National Academy of Engineering's Grand Challenge of providing access to clean water. Both problems are designed to encourage students to progress through the problem solving cycle, with parts of the solution asking students to conceptualize the system, execute calculations, and reflect on the interpretation of results. The effectiveness of this pedagogical intervention will be evaluated to determine whether this type of problem structure promotes heightened problem solving performance.

In the future, this research will be utilized in a module designed to explicitly teach students problem solving skills. The rubric will be used to provide feedback to students. In the same effort, student's perceptions of the form of feedback will be assessed.

Additionally, instructional activities will be designed that focus on addressing problem solving tasks and showed the biggest performance disparities across populations in attempts to "level the playing field" of entering students. Specifically these include 1) translating information from the problem statement into an understanding of the problem, 2) accurate unit derivation, and 3) utilizing strategies to approaching the problem that are more advanced than plug and chug or guess and check approaches.

Other researchers are encouraged to test the generalizability of this problem solving assessment method by utilizing it to assess performance in other disciplines or for other types of problems such as ill-defined project based problems.

APPENDICES

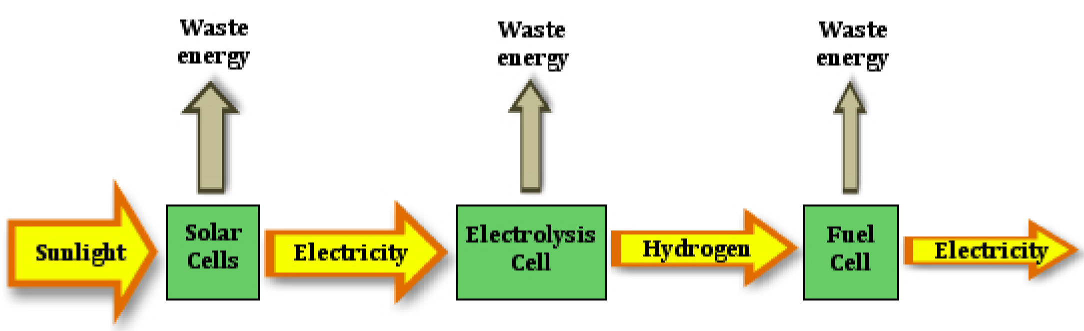
Appendix A

Solar Efficiency Problem

One problem with solar energy is that any given point on the planet is illuminated by the sun for only half of the time at best. It would be helpful, therefore, if there was a simple, affordable, and efficient means for storing any excess energy generated on sunny days for use during the night, or on cloudy days.

You are investigating the electrodes used in electrolysis cells as part of a three-stage process for solar energy collection and storage.

1. Convert sunlight to electricity with photovoltaic cells.
2. Use the electricity generated in an electrolysis cell to split water into its component elements, hydrogen, and oxygen. The hydrogen can be stored indefinitely. The oxygen can simply be released into the atmosphere.
3. Use a fuel cell to recombine the stored hydrogen with oxygen from the atmosphere to generate electricity.



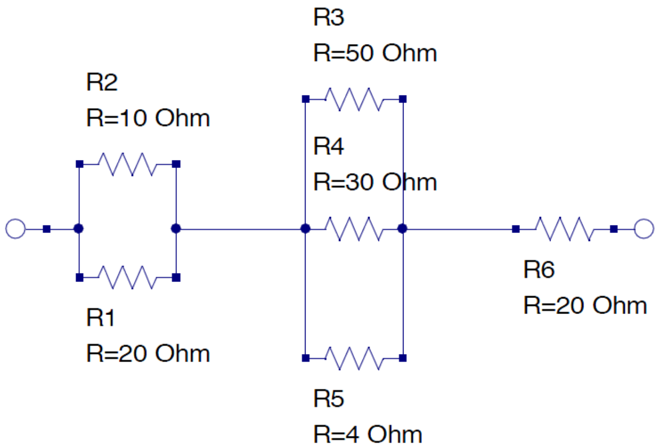
You have obtained an array of new high efficiency thin film photovoltaic cells with an efficiency of 41%. The efficiency of fuel cells varies with the current demands placed on them, but the cells you have obtained yield an overall efficiency of 37% at the anticipated load.

Assume the total solar power on the solar cells is 2000 watts. You conduct four experiments, each with a different alloy of palladium, platinum, gold, copper, and/or silver for the electrodes in the electrolysis cell. The final output power from the fuel cell is measured for each case, and the results are tabulated below. Determine the efficiency of each electrolysis cell and complete the table.

APPENDIX B

EQUIVALENT CIRCUITS PROBLEM

An electrical engineer hands us the mystery circuit shown below. This circuit has a 12 V generator connected to it to generate some unknown current (measured in amperes, A). In our possession, we have 40 Ω, 50 Ω, and 70 Ω resistors (one of each) and two voltage generators (one of each: 10 volt, 15 volt.) Remember: V = I R and 1 V = 1 A Ω



Determine the following:

a) The effective resistance of the mystery circuit in Ohms [Ω].
b) The current generated by the mystery circuit in amperes [A].
c) Select a combination (single, parallel, or series) of resistors and a single voltage generator that when connected will generate the closest current to the mystery circuit.

APPENDIX C

HYDROSTATIC PRESSURE PROBLEMS

ORIGINAL PRESSURE PROBLEM (FALL 2009):

A cylindrical tank filled to a height of 25 feet with tribromoethylene has been pressurized to 2 atmospheres ($P_{surface}$ = 2 atmospheres). The total pressure in at the bottom of the tank is 4 atmospheres. Determine the density of tribromoethylene in units of kilograms per cubic meter.

SHOW ALL OF YOUR WORK. If you do any calculations, write the calculation out in Muse*Ink*.

ALTERNATIVE PRESSURE PROBLEM (SPRING 2011):

A cylindrical tank filled with acetic acid (vinegar) has been pressurized to 3 atmospheres ($P_{surface}$ = 3 atmospheres) for processing. The total pressure at the bottom of the tank is 5 atmospheres. If the density of acetic acid is 1.01 grams per milliliter, determine the height of the liquid in the tank in units of feet.

SHOW ALL OF YOUR WORK. If you do any calculations, write the calculation out in Muse*Ink*.

APPENDIX D

CODING SCHEME

Process Element Codes

Knowledge Access

Code	Description
Identify equation	Equation with variables, no values
Implicit equation identification	No formal equation shown, values inserted initially
Identified assumption	Explicit statement of assumption or self-imposed constraint
Identify prior knowledge	Identifying outside knowledge to solve the problem
Identify conversion factor	list conversion
Use conversion factor	Ex 1ft = 12 in 4ft=>in=48 in

Knowledge Generation

Code	Description
Draw a picture / diagram	Flow diagram, schematic, sketch, Venn diagram, etc
Make a table	Organizing like data in lists
Relate variables	Assigning relationships in the system, show connections, insert knowns values in diagram
Manipulate equation	Solving an equation for another variable
Derive units	Ex: 4 ft*12in/1ft=48 in
Plug values in equation	Inserting given or derived values
Document math	Documentation of mathematical calculations
Solve intermediate value	Getting a sub answer

Self-Management

Code		Description
Planning	Restate problem	Summarize in phrases or sentences
	Identify known value	Defining variables by given values from problem statement
	Identify unknown value	What they are looking to solve for
	Identify constraint	Information from problem statement (Ex: only one of each type of resistors)
	Identify final answer	Boxed/underline/circle answer
Revising	Labeling / Renaming	Clarifying documentation, relabeling variables (adding subscripts)
	Erase work	Indicates transition (does not include penmanship corrections)
	Abandon process / Start over	Completely changing gears
Evaluating	Check accuracy	Plug answer back in and check
Monitoring	Identify error	Corrects or erases that contained a previous error

Error Codes

Conceptual Errors

Code	Description
Incorrectly relate variables	EX: P1out=P2in, P2out=P3in
Misuse governing equation	Error in equation EX: flipped variables or sign
Incorrect visual/graphic representation	Misrepresents underlying concepts
Incorrect assumptions	Places or misuses constraints on the system or assumptions not given in problem statement

Mechanical Errors

Code	Description
Incorrectly manipulate equation	Algebra problem
Incorrect calculation	Plug numbers in calculator wrong
Incorrect unit derivation	Error in deriving units

Management Errors

Code	Description
Incorrect known value	Insert wrong number for variable
Incorrect unknown value	Solve for wrong variable
Ignored problem constraints	Does not conform to constraints given in problem statement
Irrelevant information	Use values that are not given and not needed
Inconsistent transcription	Use if correct information is rewritten incorrectly (miscopy)
Inconsistent units	Mismatch of units in a calculation (such as mixing English and SI units in an equation)
Incorrect unit assignment	Label wrong units on value (arbitrarily with no other work)
Using incorrectly generated information	Using incorrect equation or value calculated in previous part of problem
Missing Units Throughout	No use of units (or few) in calculations throughout
Erasing correct work	Correcting "mistake" that is not really wrong

Approach Strategy Codes

Code	Description
Plug and chug	Plug numbers into equations without understanding why
Guess and Check	Try values and see what gives good answers
Work Backwards	Choose steps based on known solution
Utilize a similar problem	Refer to or work from book example
Segmentation	Discovering or acknowledging multiple parts to problem. Aka problem decomposition or subgoaling
Chunking	Collapsing multiple parts into one step
Means-end analysis	Work to minimize differences between goal and starting point
Forward chaining	Planning out path to solve problem
Specialization/Extreme cases	Considering abstract or extreme forms of problem

Solution Accuracy Codes

Code	Description
Correct Answer	Correctly calculated final answer
Correct but Missing/Incorrect Units	Correct value with no or incorrect units
Incorrect Answer	Solved for wrong variable, skipped steps
Gave up	Failed to produce an answer

APPENDIX E

INTERNAL PROCESS MEASURES AND CALCULATIONS

Problem Solving Stage		Internal Process Measures		Calculation
1	Recognize / identify the problem	Explicit unknown value	Completed	IIf(Identify unknowns>0,1,0)
		Correct Unknown value	Accuracy	IIf(Count([Incorrect unknown value]>0,0,1)
		# Tries to get correctunknown	Efficiency	IIf(Count([Incorrect unknown value]>0, “NA”, Count([Incorrect unknown value-HIT]))
2a	Define the problem	Explicit definition	Completed	Sum(IIf(Count([Restate problem]>0,1,0)) + IIf(Count([Identify assumption]>0,1,0))+ IIf(Count([Identify constraint]>0,1,0)))
		Correct definition	Accuracy	IIf(Count([Incorrect constraint]>0,0, IIf(Count([Incorrect assumption]>0,0,1))
		# Tries to get correct definition	Efficiency	IIf(Count([Incorrect constraint]>0, “NA”, IIf(Count([Incorrect assumption]>0, “NA”, Sum(Count([Incorrect constraint -HIT])+ Count([Incorrect assumption -HIT])))
2b	Represent the problem	Explicit visual	Completed	IIf([Draw a picture / diagram]>0, IIf([Relate variables]>0, 1,0.5),0)
		Correct representation	Accuracy	IIf(([Draw a picture/diagram]+[Relate variables])>0, IIf(([Incorrect visual/graphic representation] + [Incorrectly relate variables])>0,0,1),0)
		# Tries to get correct representation	Efficiency	IIf(Count([Incorrect visual representation]>0, “NA”, IIf(Count([Incorrectly relate variables]>0, “NA”, Sum(Count([Incorrect visual representation-HIT])+ Count([Incorrectly relate variables -HIT])))
3	Develop a solution strategy	Approach Strategy Used	Efficiency	IIf([Plug and chug], 0, IIf([Guess and check], 0, IIf([Segmentation],0.5, IIf([Means end analysis],0.5, IIf([Chunking],1, IIf([Forward chaining],1, “other”)))
4	Organize knowledge about the problem	Explicit knowns and Equations	Completed	Sum(IIf(Count([Identify known values]>0,1,0)) + IIf(Count([Identify equation]>0,1,0)))
		Correct knowns	Accuracy	IIf(Count([Incorrect known value]>0,0,1)
		Correct equation	Accuracy	IIf(Count([Misuse governing equation]>0,0,1)
		# Tries to get correct knowns	Efficiency	IIf(Count([Incorrect known value]>0, “NA”, Count([Incorrect known value-HIT]))
		# Tries to get correct equation	Efficiency	IIf(Count([Misuse equation]>0, “NA”, Count([Misuse equation -HIT]))

5	Allocate resources (Execution)	Execute tasks to arrive at solutions	Completed	Sum(IIf(Count([Manipulate equation]>0,1,0)) + IIf(Count(Derive Units]>0,1,0)) + IIf(Count([Use conversion factor]>0,1,0)) + IIf(Count([Plug values in equation]>0,1,0)) + IIf(Count([Document math]>0,1,0)) + IIf(Count([Solve intermediate value]>0,1,0)))
		Correct Execution - Mechanical	Accuracy	IIf(Count([Incorrectly manipulate equation]>0,0, IIf(Count([Incorrect calculation]>0,0, IIf(Count([Incorrect unit derivation]>0,0,1))))
		# Tries to get correct mechanical execution	Efficiency	IIf(Sum(Count([Incorrectly manipulate equation]) + Count([Incorrect calculation]) + Count(Incorrect unit derivation]))>0, “NA”, Sum(Count([Incorrectly manipulate equation-HIT]) + Count(Incorrect calculation-HIT]) + Count(Incorrect unit derivation-HIT])))
		Correct Execution - Management	Accuracy	IIf(Count([Inconsistent transcription]>0,0, IIf(Count([Inconsistent units]>0,0, IIf(Count([Incorrect unit assignment]>0,0, IIf(Count([Missing units throughout]>0,0,1))))
		# Tries to get correct management execution	Efficiency	IIf(Sum(Count([Inconsistent transcription]) + Count([Inconsistent units]) + Count([Incorrect unit assignment]) + Count([Missing units throughout]))>0, “NA”, Sum(Count([Inconsistent transcription-HIT]) + Count([Inconsistent units-HIT]) + Count([Incorrect unit assignment-HIT]) + Count([Missing units throughout-HIT]))
		Number of tasks	Efficiency	Count[Task]
		Overprocessing	Efficiency	IIf(Count[Erasing correct work]>0,1,0)
		Overproduction	Efficiency	IIf(Count[Irrelevant Information]>0,1,0)
6	Monitor progress toward the goals	Sensitivity (A’)	Accuracy	$A' = 1 - \frac{1}{4}\left[\frac{P(FA)}{P(H)} + \frac{1-P(H)}{1-P(FA)}\right]$
		Hit rate	Accuracy	$\frac{\text{Count}[\text{Errors HIT}]}{\text{Count}[\text{Errors}] + \text{Count}[\text{Errors HIT}]}$
		False alarm rate	Efficiency	$\frac{\text{Count}[\text{False Alarm}]}{\text{Count}[\text{Tasks}]}$
7	Evaluate the solution	Check accuracy	Completed	IIf([Check accuracy]>0,1,0)
		Indicate answer	Completed	IIf([Identify final answer]>0,1,0)

Appendix F

Outcome Measures and Calculations

Problem Solving Outcome Under Assessment		Performance Measures	Calculation
1	Solution Accuracy (Product)	Answer Accuracy	* Average [Answer State]
		Conceptual Errors	Count[Conceptual Errors (not corrected)]
		Mechanical Errors	Count[Mechanical Errors (not corrected)]
		Management Errors	Count[Management Errors (not corrected)]
2	Solution Efficiency (Process)	Error Rate	$\frac{\text{Count}[\text{Errors}]}{\text{Count}[\text{Tasks}]}$
		Time to complete	[End time]-[Start time]
3	Stress Measures (Person)	NASA-TLX (5)	Sum([Mental Demand]+[Temporal Demand]+[Performance]+[Effort]+[Frustration])
		Mental Demand	[0,20] (Self-report)
		Temporal Demand	[0,20] (Self-report)
		Performance	[0,20] (Self-report)
		Effort	[0,20] (Self-report)
		Frustration	[0,20] (Self-report)

APPENDIX G

ODDS RATIOS BY PROBLEM SOLVING SUCCESS

Collective Assessment for Fall 2009

	Correct : did contain	Correct : did not contain	Incorrect : did contain	Incorrect : did not contain	Odds Ratio: Correct were more likely	Odds Ratio: Incorrect were more likely	SE	p-value
Identify equation	16	5	40	7	0.56	1.79	0.6	0.262
Implicit equation identification	8	13	31	16	0.32	3.15	0.5	0.039
Identified assumption	1	20	1	46	2.30	0.43	1.2	0.312
Identify prior knowledge	2	19	1	46	4.84	0.21	1.1	0.134
Identify conversion factor	1	20	0	47	6.95	0.14	1.7	0.201
Use conversion factor	10	11	12	35	2.65	0.38	0.5	0.078
Draw a picture / diagram	11	10	15	32	2.35	0.43	0.5	0.108
Make a table	1	20	2	45	1.13	0.89	1.1	0.397
Relate variables	14	7	15	32	4.27	0.23	0.5	0.012
Manipulate equation	0	21	12	35	0.07	15.14	1.5	0.072
Derive units	5	16	7	40	1.79	0.56	0.6	0.262
Plug values in equation	16	5	40	7	0.56	1.79	0.6	0.262
Document math	20	1	29	18	12.41	0.08	0.9	0.008
Solve intermediate value	16	5	42	5	0.38	2.63	0.7	0.141
Identify unknown value	7	14	4	43	5.38	0.19	0.7	0.017
Identify final answer	15	6	31	16	1.29	0.78	0.6	0.359
Erase work	13	8	29	18	1.01	0.99	0.5	0.399
Abandon process / Start over	0	21	4	43	0.22	4.45	1.5	0.245
Check accuracy	1	20	2	45	1.13	0.89	1.1	0.397

Identify errors	16	5	45	2	0.14	7.03	0.8	0.023
Incorrectly relate variables	6	15	16	31	0.78	1.29	0.6	0.359
Misuse governing equation	4	17	13	34	0.62	1.63	0.6	0.293
Incorrect visual/graphic representation	0	21	1	46	0.72	1.39	1.7	0.391
Incorrect assumptions	0	21	1	46	0.72	1.39	1.7	0.391
Incorrectly manipulate equation	0	21	1	46	0.72	1.39	1.7	0.391
Incorrect calculation	1	20	9	38	0.21	4.74	0.9	0.096
Incorrect unit derivation	1	20	4	43	0.54	1.86	1.0	0.326
Incorrect known value	3	18	5	42	1.40	0.71	0.7	0.360
Incorrect unknown value	1	20	4	43	0.54	1.86	1.0	0.326
Ignored problem constraints	0	21	8	39	0.11	9.25	1.5	0.129
Irrelevant information	4	17	9	38	0.99	1.01	0.6	0.399
Inconsistent transcription	1	20	5	42	0.42	2.38	1.0	0.265
Inconsistent units	7	14	11	36	1.64	0.61	0.6	0.272
Incorrect unit assignment	2	19	3	44	1.54	0.65	0.9	0.352
Using incorrectly generated information	1	20	15	32	0.11	9.38	0.9	0.018
Missing Units Throughout	1	20	1	46	2.30	0.43	1.2	0.312
Erasing correct work	7	14	15	32	1.07	0.94	0.5	0.396
Plug and chug	1	20	18	29	0.08	12.41	0.9	0.008
Guess and Check	0	21	11	36	0.07	13.55	1.5	0.083
Segmentation	8	13	13	34	1.61	0.62	0.5	0.272
Means-end analysis	7	14	2	45	11.25	0.09	0.8	0.004
Chunking	3	18	14	33	0.39	2.55	0.7	0.147
Forward chaining	3	18	6	41	1.14	0.88	0.7	0.392

Collective Assessment for Spring 2011

	Correct : did contain	Correct : did not contain	Incorrect : did contain	Incorrect : did not contain	Odds Ratio: Correct were more likely	Odds Ratio: Incorrect were more likely	SE	p-value
Identify equation	61	0	14	1	12.72	0.08	1.7	0.123
Implicit equation identification	15	46	9	6	0.22	4.60	0.6	0.014
Identify prior knowledge	7	54	1	14	1.81	0.55	0.9	0.327
Identify conversion factor	14	47	2	13	1.94	0.52	0.8	0.271
Use conversion factor	27	34	4	11	2.18	0.46	0.6	0.177
Draw a picture / diagram	26	35	12	3	0.19	5.38	0.7	0.015
Relate variables	27	34	11	4	0.29	3.46	0.6	0.051
Manipulate equation	18	43	6	9	0.63	1.59	0.6	0.289
Derive units	23	38	3	12	2.42	0.41	0.7	0.162
Plug values in equation	60	1	14	1	4.29	0.23	1.2	0.189
Document math	42	19	11	4	0.80	1.24	0.6	0.375
Solve intermediate value	61	0	14	1	12.72	0.08	1.7	0.123
Restate problem	33	28	8	7	1.03	0.97	0.6	0.398
Identify known value	51	10	13	2	0.78	1.27	0.8	0.379
Identify constraint	0	61	2	13	0.04	22.78	1.6	0.056
Identify final answer	54	7	12	3	1.93	0.52	0.7	0.263
Erase work	50	11	13	2	0.70	1.43	0.8	0.357
Abandon process / Start over	8	53	1	14	2.11	0.47	0.9	0.289
Check accuracy	6	55	2	13	0.71	1.41	0.8	0.364
Identify errors	55	6	15	0	0.28	3.63	1.5	0.275
Incorrectly relate variables	22	39	10	5	0.28	3.55	0.6	0.040
Misuse governing equation	17	44	6	9	0.58	1.73	0.6	0.257

Incorrect visual/graphic representation	2	59	0	15	1.30	0.77	1.6	0.393
Incorrectly manipulate equation	1	60	0	15	0.77	1.30	1.7	0.394
Incorrect calculation	6	55	2	13	0.71	1.41	0.8	0.364
Incorrect unit derivation	12	49	1	14	3.43	0.29	0.9	0.161
Incorrect known value	13	48	4	11	0.74	1.34	0.6	0.358
Incorrect unknown value	14	47	2	13	1.94	0.52	0.8	0.271
Ignored problem constraints	4	57	3	12	0.28	3.56	0.8	0.105
Irrelevant information	14	47	1	14	4.17	0.24	0.9	0.116
Inconsistent transcription	8	53	1	14	2.11	0.47	0.9	0.289
Inconsistent units	16	45	2	13	2.31	0.43	0.7	0.212
Incorrect unit assignment	11	50	0	15	7.06	0.14	1.5	0.166
Using incorrectly generated information	20	41	3	12	1.95	0.51	0.7	0.240
Missing Units Throughout	3	58	0	15	1.85	0.54	1.5	0.368
Erasing correct work	19	42	3	12	1.81	0.55	0.7	0.268
Plug and chug	4	57	7	8	0.08	12.47	0.7	0.001
Guess and Check	14	47	4	11	0.82	1.22	0.6	0.380
Segmentation	21	40	9	6	0.35	2.86	0.6	0.075
Means-end analysis	17	44	1	14	5.41	0.18	0.9	0.069
Chunking	14	47	3	12	1.19	0.84	0.7	0.386
Forward chaining	5	56	0	15	3.02	0.33	1.5	0.305

Collective Assessment for Fall 2009 and Spring 2011 Combined

	Correct : did contain	Correct : did not contain	Incorrect : did contain	Incorrect : did not contain	Odds Ratio Correct were more likely	Odds Ratio Incorrect were more likely	SE	p-value
Identify equation	77	5	54	8	2.28	0.44	0.6	0.143
Implicit equation identification	23	59	40	22	0.21	4.66	0.4	0.000
Identified assumption	1	81	1	61	0.75	1.33	1.2	0.387
Identify prior knowledge	9	73	2	60	3.70	0.27	0.7	0.081
Identify conversion factor	15	67	2	60	6.72	0.15	0.7	0.010
Use conversion factor	37	45	16	46	2.36	0.42	0.4	0.024
Draw a picture / diagram	37	45	27	35	1.07	0.94	0.3	0.392
Make a table	1	81	2	60	0.37	2.70	1.0	0.254
Relate variables	41	41	26	36	1.38	0.72	0.3	0.250
Manipulate equation	18	64	18	44	0.69	1.45	0.4	0.247
Derive units	28	54	10	52	2.70	0.37	0.4	0.021
Plug values in equation	76	6	54	8	1.88	0.53	0.6	0.207
Document math	62	20	40	22	1.71	0.59	0.4	0.138
Solve intermediate value	77	5	56	6	1.65	0.61	0.6	0.283
Identify known value	63	19	38	24	2.09	0.48	0.4	0.052
Identify unknown value	53	29	14	48	6.27	0.16	0.4	0.000
Identify final answer	69	13	43	19	2.35	0.43	0.4	0.043
Labeling / Renaming	43	39	31	31	1.10	0.91	0.3	0.382
Erase work	63	19	42	20	1.58	0.63	0.4	0.189
Abandon process / Start over	8	74	5	57	1.23	0.81	0.6	0.373
Check accuracy	7	75	4	58	1.35	0.74	0.6	0.354
Identify errors	71	11	60	2	0.22	4.65	0.7	0.041

Incorrectly relate variables	28	54	26	36	0.72	1.39	0.3	0.251
Misuse governing equation	21	61	19	43	0.78	1.28	0.4	0.318
Incorrect visual/graphic representation	2	80	1	61	1.53	0.66	1.0	0.368
Incorrect assumptions	0	82	1	61	0.25	4.02	1.6	0.278
Incorrectly manipulate equation	1	81	1	61	0.75	1.33	1.2	0.387
Incorrect calculation	7	75	11	51	0.43	2.31	0.5	0.100
Incorrect unit derivation	13	69	5	57	2.15	0.47	0.5	0.144
Incorrect known value	16	66	9	53	1.43	0.70	0.4	0.290
Incorrect unknown value	15	67	6	56	2.09	0.48	0.5	0.135
Ignored problem constraints	4	78	11	51	0.24	4.21	0.6	0.019
Irrelevant information	18	64	10	52	1.46	0.68	0.4	0.269
Inconsistent transcription	9	73	6	56	1.15	0.87	0.5	0.386
Inconsistent units	23	59	13	49	1.47	0.68	0.4	0.246
Incorrect unit assignment	13	69	3	59	3.71	0.27	0.6	0.044
Using incorrectly generated information	21	61	18	44	0.84	1.19	0.4	0.359
Missing Units Throughout	4	78	1	61	3.13	0.32	1.0	0.196
Erasing correct work	26	56	18	44	1.13	0.88	0.4	0.375
Plug and chug	5	77	25	37	0.10	10.41	0.5	0.000
Guess and Check	14	68	15	47	0.65	1.55	0.4	0.226
Segmentation	29	53	22	40	0.99	1.01	0.3	0.399
Means-end analysis	24	58	3	59	8.14	0.12	0.6	0.001
Chunking	17	65	17	45	0.69	1.44	0.4	0.255
Forward chaining	8	74	6	56	1.01	0.99	0.6	0.399

Solar Efficiency Problem for Fall 2009 and Spring 2011 Combined

	Correct : did contain	Correct : did not contain	Incorrect : did contain	Incorrect : did not contain	Odds Ratio Correct were more likely	Odds Ratio Incorrect were more likely	SE	p-value
Identify equation	29	4	13	4	2.23	0.45	0.7	0.223
Implicit equation identification	6	27	8	9	0.25	4.00	0.6	0.039
Identified assumption	1	32	1	16	0.50	2.00	1.2	0.337
Identify prior knowledge	0	33	0	17	0.52	1.91	2.0	0.379
Identify conversion factor	0	33	0	17	0.52	1.91	2.0	0.379
Use conversion factor	1	32	0	17	1.62	0.62	1.7	0.383
Draw a picture / diagram	13	20	6	11	1.19	0.84	0.6	0.382
Make a table	1	32	2	15	0.23	4.27	1.1	0.161
Relate variables	19	14	7	10	1.94	0.52	0.6	0.213
Manipulate equation	12	21	1	16	9.14	0.11	0.9	0.023
Derive units	0	33	1	16	0.16	6.09	1.7	0.221
Plug values in equation	29	4	14	3	1.55	0.64	0.8	0.340
Document math	20	13	7	10	2.20	0.46	0.6	0.165
Solve intermediate value	31	2	17	0	0.36	2.78	1.6	0.323
Identify known value	28	5	13	4	1.72	0.58	0.7	0.299
Identify unknown value	23	10	5	12	5.52	0.18	0.6	0.010
Identify final answer	32	1	14	3	6.86	0.15	1.0	0.069
Labeling / Renaming	23	10	11	6	1.25	0.80	0.6	0.373
Erase work	29	4	13	4	2.23	0.45	0.7	0.223
Abandon process / Start over	7	26	4	13	0.88	1.14	0.7	0.391
Check accuracy	2	31	0	17	2.78	0.36	1.6	0.323
Identify errors	30	3	16	1	0.63	1.60	1.0	0.359

Incorrectly relate variables	22	11	14	3	0.43	2.33	0.7	0.191
Misuse governing equation	16	17	5	12	2.26	0.44	0.6	0.166
Incorrect visual/graphic representation	1	32	0	17	1.62	0.62	1.7	0.383
Incorrect assumptions	0	33	1	16	0.16	6.09	1.7	0.221
Incorrectly manipulate equation	0	33	0	17	0.52	1.91	2.0	0.379
Incorrect calculation	1	32	2	15	0.23	4.27	1.1	0.161
Incorrect unit derivation	0	33	0	17	0.52	1.91	2.0	0.379
Incorrect known value	11	22	5	12	1.20	0.83	0.6	0.382
Incorrect unknown value	12	21	3	14	2.67	0.38	0.7	0.147
Ignored problem constraints	1	32	0	17	1.62	0.62	1.7	0.383
Irrelevant information	16	17	5	12	2.26	0.44	0.6	0.166
Inconsistent transcription	2	31	2	15	0.48	2.07	0.9	0.297
Inconsistent units	0	33	0	17	0.52	1.91	2.0	0.379
Incorrect unit assignment	1	32	0	17	1.62	0.62	1.7	0.383
Using incorrectly generated information	6	27	7	10	0.32	3.15	0.6	0.083
Missing Units Throughout	4	29	0	17	5.34	0.19	1.5	0.218
Erasing correct work	13	20	10	7	0.46	2.20	0.6	0.165
Plug and chug	1	32	2	15	0.23	4.27	1.1	0.161
Guess and Check	2	31	3	14	0.30	3.32	0.9	0.160
Segmentation	27	6	11	6	2.45	0.41	0.7	0.157
Means-end analysis	0	33	0	17	0.52	1.91	2.0	0.379
Chunking	3	30	1	16	1.60	0.63	1.0	0.359
Forward chaining	0	33	0	17	0.52	1.91	2.0	0.379

Equivalent Circuit Problem for Fall 2009 and Spring 2011 Combined

	Correct : contained	Correct : did not contain	Incorrect : contained	Incorrect : did not contain	Odds Ratio Correct were more likely	Odds Ratio Incorrect were more likely	SE	p-value
Identify equation	15	0	27	3	3.95	0.25	1.5	0.269
Implicit equation identification	15	0	30	0	0.51	1.97	2.0	0.377
Identified assumption	0	15	0	30	1.97	0.51	2.0	0.377
Identify prior knowledge	0	15	0	30	1.97	0.51	2.0	0.377
Identify conversion factor	2	13	1	29	4.46	0.22	1.1	0.154
Use conversion factor	3	12	5	25	1.25	0.80	0.8	0.382
Draw a picture / diagram	10	5	13	17	2.62	0.38	0.6	0.129
Make a table	0	15	0	30	1.97	0.51	2.0	0.377
Relate variables	8	7	12	18	1.71	0.58	0.6	0.274
Manipulate equation	3	12	17	13	0.19	5.23	0.7	0.025
Derive units	0	15	1	29	0.63	1.58	1.7	0.384
Plug values in equation	14	1	26	4	2.15	0.46	1.0	0.297
Document math	13	2	22	8	2.36	0.42	0.8	0.223
Solve intermediate value	15	0	28	2	2.72	0.37	1.6	0.327
Identify known value	7	8	13	17	1.14	0.87	0.6	0.390
Identify unknown value	5	10	5	25	2.50	0.40	0.7	0.172
Identify final answer	12	3	21	9	1.71	0.58	0.7	0.301
Labeling / Renaming	4	11	12	18	0.55	1.83	0.7	0.264
Erase work	12	3	21	9	1.71	0.58	0.7	0.301
Abandon process / Start over	0	15	1	29	0.63	1.58	1.7	0.384
Check accuracy	1	14	3	27	0.64	1.56	1.0	0.364
Identify errors	11	4	30	0	0.04	23.87	1.5	0.047

Incorrectly relate variables	3	12	9	21	0.58	1.71	0.7	0.301
Misuse governing equation	3	12	12	18	0.38	2.67	0.7	0.152
Incorrect visual/graphic representation	1	14	1	29	2.07	0.48	1.2	0.332
Incorrect assumptions	0	15	0	30	1.97	0.51	2.0	0.377
Incorrectly manipulate equation	1	14	1	29	2.07	0.48	1.2	0.332
Incorrect calculation	3	12	8	22	0.69	1.45	0.7	0.349
Incorrect unit derivation	0	15	0	30	1.97	0.51	2.0	0.377
Incorrect known value	3	12	3	27	2.25	0.44	0.8	0.247
Incorrect unknown value	2	13	3	27	1.38	0.72	0.9	0.373
Ignored problem constraints	3	12	11	19	0.43	2.32	0.7	0.198
Irrelevant information	0	15	2	28	0.37	2.72	1.6	0.327
Inconsistent transcription	2	13	3	27	1.38	0.72	0.9	0.373
Inconsistent units	1	14	0	30	6.31	0.16	1.7	0.216
Incorrect unit assignment	1	14	0	30	6.31	0.16	1.7	0.216
Using incorrectly generated information	2	13	9	21	0.36	2.79	0.8	0.172
Missing Units Throughout	0	15	1	29	0.63	1.58	1.7	0.384
Erasing correct work	4	11	6	24	1.45	0.69	0.7	0.347
Plug and chug	3	12	15	15	0.25	4.00	0.7	0.057
Guess and Check	11	4	10	20	5.50	0.18	0.7	0.016
Segmentation	2	13	11	19	0.27	3.76	0.8	0.095
Means-end analysis	0	15	0	30	1.97	0.51	2.0	0.377
Chunking	13	2	16	14	5.69	0.18	0.8	0.033
Forward chaining	1	14	5	25	0.36	2.80	1.0	0.229

Hydrostatic Pressure Problem Assessment for Fall 2009 and Spring 2011 Combined

	Correct : did contain	Correct : did not contain	Incorrect : did contain	Incorrect : did not contain	Odds Ratio Correct were more likely	Odds Ratio Incorrect were more likely	SE	p-value
Identify equation	33	1	14	1	2.36	0.42	1.2	0.309
Implicit equation identification	2	32	2	13	0.41	2.46	1.0	0.255
Identified assumption	0	34	0	15	0.45	2.23	2.0	0.369
Identify prior knowledge	9	25	2	13	2.34	0.43	0.8	0.222
Identify conversion factor	13	21	1	14	8.67	0.12	0.9	0.026
Use conversion factor	33	1	11	4	12.00	0.08	1.0	0.019
Draw a picture / diagram	14	20	8	7	0.61	1.63	0.6	0.288
Make a table	0	34	0	15	0.45	2.23	2.0	0.369
Relate variables	14	20	7	8	0.80	1.25	0.6	0.373
Manipulate equation	3	31	0	15	3.44	0.29	1.5	0.289
Derive units	28	6	8	7	4.08	0.24	0.7	0.042
Plug values in equation	33	1	14	1	2.36	0.42	1.2	0.309
Document math	29	5	11	4	2.11	0.47	0.7	0.235
Solve intermediate value	31	3	11	4	3.76	0.27	0.8	0.099
Identify known value	28	6	12	3	1.17	0.86	0.7	0.390
Identify unknown value	25	9	4	11	7.64	0.13	0.7	0.004
Identify final answer	25	9	8	7	2.43	0.41	0.6	0.147
Labeling / Renaming	16	18	8	7	0.78	1.29	0.6	0.366
Erase work	22	12	8	7	1.60	0.62	0.6	0.296
Abandon process / Start over	1	33	0	15	1.39	0.72	1.7	0.391
Check accuracy	4	30	1	14	1.87	0.54	1.0	0.328
Identify errors	30	4	14	1	0.54	1.87	1.0	0.328

Incorrectly relate variables	3	31	3	12	0.39	2.58	0.8	0.206
Misuse governing equation	2	32	2	13	0.41	2.46	1.0	0.255
Incorrect visual/graphic representation	0	34	0	15	0.45	2.23	2.0	0.369
Incorrect assumptions	0	34	0	15	0.45	2.23	2.0	0.369
Incorrectly manipulate equation	0	34	0	15	0.45	2.23	2.0	0.369
Incorrect calculation	3	31	1	14	1.35	0.74	1.0	0.382
Incorrect unit derivation	13	21	5	10	1.24	0.81	0.6	0.377
Incorrect known value	2	32	1	14	0.88	1.14	1.1	0.396
Incorrect unknown value	1	33	0	15	1.39	0.72	1.7	0.391
Ignored problem constraints	0	34	0	15	0.45	2.23	2.0	0.369
Irrelevant information	2	32	3	12	0.25	4.00	0.9	0.119
Inconsistent transcription	5	29	1	14	2.41	0.41	1.0	0.265
Inconsistent units	22	12	13	2	0.28	3.55	0.8	0.105
Incorrect unit assignment	11	23	3	12	1.91	0.52	0.7	0.261
Using incorrectly generated information	13	21	2	13	4.02	0.25	0.8	0.078
Missing Units Throughout	0	34	0	15	0.45	2.23	2.0	0.369
Erasing correct work	9	25	2	13	2.34	0.43	0.8	0.222
Plug and chug	1	33	8	7	0.03	37.71	1.0	0.000
Guess and Check	1	33	2	13	0.20	5.08	1.1	0.129
Segmentation	0	34	0	15	0.45	2.23	2.0	0.369
Means-end analysis	24	10	3	12	9.60	0.10	0.7	0.002
Chunking	1	33	0	15	1.39	0.72	1.7	0.391
Forward chaining	7	27	1	14	3.63	0.28	1.0	0.159

Appendix H

Significant effects of Presence of Problem Solving Features on Problem Solving Success from the Linear Mixed Effects Models

Each table represents a separate regression model.

The intercept is representative of the neutral condition where the solution was completed for problem 1 in the first semester and did not utilize the problem feature. Each line of the table represents the impact of a change to that neutral condition. The value should only be interpreted in terms of the magnitude (large or small) and direction (positive of negative). The actual numeric value cannot be directly interpreted. Positive values are associated with correct solutions and large magnitudes indicate a stronger effect.

Problem 2-1 represents the effect attributed to problem 2 (over problem 1)

Problem 3-2 represents the effect attributed to problem 2 (over problem 2)

The effect from problem 3 over problem 1 is redundant and can be inferred from summing the effects of Problem 2-1 and Problem 3-2.

Semester Intervention-None indicated the effect attributed to the intervention

The remaining effect is the effect attributed to the problem feature where 1-0 indicates that the effect is due to the presence of the feature compared to not using the feature.

Features attributed to successful solutions

	Value	Std.Error	DF	t-value	p-value
Intercept	-0.614	0.651	78	-0.943	0.349
Problem 2-1	-4.413	0.656	78	-6.731	0.000
Problem 3-2	-2.057	0.845	78	-2.434	0.017
Semester Intervention-None	4.379	0.888	61	4.932	0.000
Use conversion factor 1-0	2.624	0.811	78	3.236	0.002

	Value	Std.Error	DF	t-value	p-value
Intercept	-1.339	0.627	78	-2.136	0.036
Problem 2-1	-2.504	0.738	78	-3.393	0.001
Problem 3-2	-0.231	0.603	78	-0.383	0.703
Semester Intervention-None	2.886	0.596	61	4.840	0.000
Document math 1-0	1.461	0.650	78	2.249	0.027

	Value	Std.Error	DF	t-value	p-value
Intercept	-0.400	0.397	78	-1.006	0.317
Problem 2-1	-1.916	0.584	78	-3.283	0.002
Problem 3-2	-0.855	0.660	78	-1.295	0.199
Semester Intervention-None	2.583	0.506	61	5.104	0.000
Means ends analysis 1-0	2.214	0.887	78	2.494	0.015

	Value	Std.Error	DF	t-value	p-value
Intercept	-0.659	0.447	78	-1.476	0.144
Problem 2-1	-3.092	0.858	78	-3.603	0.001
Problem 3-2	0.325	0.577	78	0.562	0.576
Semester Intervention-None	2.734	0.534	61	5.120	0.000
Chunking 1-0	1.868	0.828	78	2.257	0.027

Features attributed to unsuccessful solutions

	Value	Std.Error	DF	t-value	p-value
Intercept	0.004	0.670	78	0.006	0.995
Problem 2-1	-3.901	0.586	78	-6.662	0.000
Problem 3-2	0.252	0.444	78	0.567	0.573
Semester Intervention-None	4.254	0.841	61	5.059	0.000
Labeling Renaming 1-0	-1.297	0.486	78	-2.669	0.009

	Value	Std.Error	DF	t-value	p-value
Intercept	2.652	1.107	78	2.395	0.019
Problem 2-1	-3.417	0.576	78	-5.930	0.000
Problem 3-2	0.072	0.458	78	0.158	0.875
Semester Intervention-None	4.233	0.826	61	5.126	0.000
Identify errors 1-0	-3.813	1.055	78	-3.614	0.001

	Value	Std.Error	DF	t-value	p-value
Intercept	0.460	0.632	78	0.727	0.470
Problem 2-1	-3.648	0.634	78	-5.755	0.000
Problem 3-2	-0.655	0.546	78	-1.199	0.234
Semester Intervention-None	3.839	0.700	61	5.487	0.000
Incorrectly relate variables 1-0	-1.672	0.586	78	-2.850	0.006

	Value	Std.Error	DF	t-value	p-value
Intercept	-0.679	0.641	78	-1.060	0.292
Problem 2-1	-3.429	0.564	78	-6.084	0.000
Problem 3-2	2.408	0.918	78	2.622	0.011
Semester Intervention-None	4.069	0.862	61	4.719	0.000
Inconsistent units 1-0	-2.776	0.975	78	-2.847	0.006

	Value	Std.Error	DF	t-value	p-value
Intercept	-0.267	0.433	78	-0.618	0.538
Problem 2-1	-1.381	0.659	78	-2.096	0.039
Problem 3-2	0.547	0.615	78	0.889	0.377
Semester Intervention-None	2.614	0.561	61	4.656	0.000
Plug and chug 1-0	-2.323	0.723	78	-3.215	0.002

APPENDIX I

SIGNIFICANT EFFECTS OF PROCESS MEASURES

ON PROBLEM SOLVING SUCCESS FROM THE LINEAR MIXED EFFECTS MODELS

	Value	Std.Error	DF	t-value	p-value
Intercept	-0.978	0.565	78	-1.732	0.087
Problem 2-1	-3.336	0.584	78	-5.708	0.000
Problem 3-2	0.059	0.459	78	0.129	0.898
Semester	3.486	0.719	61	4.850	0.000
Correct representation 1-0	1.417	0.501	78	2.829	0.006

	Value	Std.Error	DF	t-value	p-value
Intercept	-2.646	0.899	77	-2.943	0.004
Problem 2-1	-1.857	0.751	77	-2.472	0.016
Problem 3-2	0.479	0.744	77	0.644	0.522
Semester	2.948	0.695	61	4.243	0.000
Strategy Intermediate - Basic	2.444	0.793	77	3.081	0.003
Strategy Advanced- Intermediate	3.250	1.133	77	2.870	0.005

	Value	Std.Error	DF	t-value	p-value
Intercept	-6.995	1.378	78	-5.076	0.000
Problem 2-1	-5.247	0.700	78	-7.497	0.000
Problem 3-2	0.319	0.415	78	0.768	0.445
Semester	6.691	1.218	61	5.494	0.000
Correct known values 1-0	6.414	1.169	78	5.488	0.000

	Value	Std.Error	DF	t-value	p-value
Intercept	-1.596	0.709	78	-2.251	0.027
Problem 2-1	-3.328	0.568	78	-5.862	0.000
Problem 3-2	1.064	0.486	78	2.192	0.031
Semester	4.568	0.911	61	5.013	0.000
Number of tries to achieve correct known values	3.875	0.934	78	4.149	0.000

	Value	Std.Error	DF	t-value	p-value
Intercept	-3.355	1.246	78	-2.693	0.009
Problem 2-1	-3.078	0.548	78	-5.612	0.000
Problem 3-2	0.373	0.452	78	0.824	0.412
Semester	3.881	0.793	61	4.896	0.000
Correct mechanical execution	2.811	1.119	78	2.513	0.014

	Value	Std.Error	DF	t-value	p-value
Intercept	-1.965	0.828	78	-2.373	0.020
Problem 2-1	-3.511	0.581	78	-6.046	0.000
Problem 3-2	0.913	0.539	78	1.695	0.094
Semester	4.006	0.801	61	5.002	0.000
Correct management of execution tasks	1.460	0.643	78	2.270	0.026

	Value	Std.Error	DF	t-value	p-value
Intercept	-19.922	2.629	78	-7.578	0.000
Problem 2-1	-6.546	0.810	78	-8.080	0.000
Problem 3-2	0.248	0.525	78	0.473	0.638
Semester	6.890	1.305	61	5.280	0.000
Sensitivity	22.164	2.757	78	8.039	0.000

	Value	Std.Error	DF	t-value	p-value
Intercept	-83.005	7.160	78	-11.592	0.000
Problem 2-1	-77.960	0.214	78	-364.576	0.000
Problem 3-2	-18.076	0.062	78	-292.674	0.000
Semester	61.352	9.422	61	6.511	0.000
Hit Rate	144.205	0.395	78	364.684	0.000

Appendix J

Significant effects of Outcome Measures on Problem Solving Success from the Linear Mixed Effects Model

	Value	Std.Error	DF	t-value	p-value
Intercept	0.991	0.647	78	1.532	0.130
Problem 2-1	-4.386	0.702	78	-6.251	0.000
Problem 3-2	-1.129	0.587	78	-1.924	0.058
Semester	3.967	0.730	61	5.433	0.000
Conceptual Errors	-2.502	0.525	78	-4.767	0.000

	Value	Std.Error	DF	t-value	p-value
Intercept	-0.583	0.583	78	-1.000	0.320
Problem 2-1	-3.078	0.548	78	-5.622	0.000
Problem 3-2	0.454	0.455	78	0.996	0.323
Semester	3.936	0.793	61	4.965	0.000
Mechanical Errors	-2.551	0.931	78	-2.741	0.008

	Value	Std.Error	DF	t-value	p-value
Intercept	0.947	0.866	78	1.092	0.278
Problem 2-1	-6.021	0.783	78	-7.692	0.000
Problem 3-2	0.097	0.456	78	0.212	0.833
Semester	6.104	1.177	61	5.187	0.000
Management Errors	-1.397	0.246	78	-5.671	0.000

	Value	Std.Error	DF	t-value	p-value
Intercept	6.836	1.532	78	4.462	0.000
Problem 2-1	-9.887	1.056	78	-9.367	0.000
Problem 3-2	-0.260	0.470	78	-0.554	0.581
Semester	6.499	1.716	61	3.788	0.000
Error Rate	-34.579	4.106	78	-8.421	0.000

APPENDIX K

SIGNIFICANT EFFECTS OF PROBLEM SOLVING FEATURES ON MENTAL WORKLOAD MEASURES FROM LINEAR MIXED EFFECTS MODELS

NOTES ON INTERPRETING RESULTS:

Each table represents a separate regression model.

The intercept is representative of the neutral condition where the solution was completed for problem 1 and did not utilize the problem feature. Each line of the table represents the impact of a change to that neutral condition. The value should only be interpreted in terms of the magnitude (large or small) and direction (positive of negative). The actual numeric value cannot be directly interpreted. Positive values are associated with correct solutions and large magnitudes indicate a stronger effect.

Problem 2-1 represents the effect attributed to problem 2 (over problem 1)
Problem 3-2 represents the effect attributed to problem 2 (over problem 2)
The effect from problem 3 over problem 1 is redundant and can be inferred from summing the effects of Problem 2-1 and Problem 3-2.

The remaining effect is the effect attributed to the problem feature where 1-0 indicates that the effect is due to the presence of the feature compared to not using the feature.

Significant Effects of Problem Solving Features on Overall Mental Workload

	Value	Std.Error	DF	t-value	p-value
Intercept	76.966	14.528	34	5.298	0.000
Problem 2-1	-5.248	3.599	34	-1.458	0.154
Problem 3-2	-3.521	3.390	34	-1.039	0.306
Identify equation 1-0	-30.281	14.158	34	-2.139	0.040

	Value	Std.Error	DF	t-value	p-value
Intercept	69.051	11.186	34	6.173	0.000
Problem 2-1	-5.502	3.626	34	-1.518	0.138
Problem 3-2	-3.386	3.383	34	-1.001	0.324
Plug values in equation 1-0	-22.734	10.889	34	-2.088	0.044

	Value	Std.Error	DF	t-value	p-value
Intercept	36.022	5.922	34	6.082	0.000
Problem 2-1	0.728	4.178	34	0.174	0.863
Problem 3-2	-3.279	3.440	34	-0.953	0.347
Identify known value 1-0	10.859	5.247	34	2.069	0.046

	Value	Std.Error	DF	t-value	p-value
Intercept	41.747	3.786	34	11.027	0.000
Problem 2-1	-1.662	3.606	34	-0.461	0.648
Problem 3-2	1.455	3.948	34	0.369	0.715
Misuse governing equation 1-0	8.677	4.116	34	2.108	0.043

	Value	Std.Error	DF	t-value	p-value
Intercept	46.786	3.019	34	15.495	0.000
Problem 2-1	-3.605	3.500	34	-1.030	0.310
Problem 3-2	-8.792	4.305	34	-2.042	0.049
Incorrect unit derivation 1-0	11.804	5.557	34	2.124	0.041

	Value	Std.Error	DF	t-value	p-value
Intercept	43.163	2.999	34	14.393	0.000
Problem 2-1	-2.148	3.143	34	-0.683	0.499
Problem 3-2	-7.016	3.179	34	-2.207	0.034
Using incorrectly generated information 1-0	15.246	3.831	34	3.980	0.000

Significant Effects of Problem Solving Features on Mental Demand

	Value	Std.Error	DF	t-value	p-value
Intercept	21.883	3.931	34	5.566	0.000
Problem 2-1	-2.905	0.976	34	-2.978	0.005
Problem 3-2	-0.879	0.919	34	-0.956	0.346
Identify equation 1-0	-10.180	3.832	34	-2.657	0.012

	Value	Std.Error	DF	t-value	p-value
Intercept	11.526	0.810	34	14.238	0.000
Problem 2-1	-2.914	0.990	34	-2.944	0.006
Problem 3-2	-5.586	2.096	34	-2.666	0.012
Use conversion factor 1-0	4.914	1.919	34	2.561	0.015

	Value	Std.Error	DF	t-value	p-value
Intercept	18.374	3.052	34	6.020	0.000
Problem 2-1	-2.924	1.006	34	-2.908	0.006
Problem 3-2	-0.851	0.939	34	-0.907	0.371
Plug values in equation 1-0	-6.772	2.971	34	-2.279	0.029

	Value	Std.Error	DF	t-value	p-value
Intercept	8.638	1.639	34	5.270	0.000
Problem 2-1	-1.043	1.197	34	-0.872	0.390
Problem 3-2	-0.931	0.998	34	-0.933	0.358
Identify known value 1-0	3.160	1.475	34	2.143	0.039

	Value	Std.Error	DF	t-value	p-value
Intercept	11.162	0.835	34	13.362	0.000
Problem 2-1	-2.063	1.054	34	-1.957	0.059
Problem 3-2	-1.634	1.055	34	-1.549	0.131
Using incorrectly generated information 1-0	2.482	1.146	34	2.166	0.037

Significant Effects of Problem Solving Features on Temporal Demand

	Value	Std.Error	DF	t-value	p-value
Intercept	5.964	1.875	34	3.181	0.003
Problem 2-1	2.112	1.476	34	1.431	0.162
Problem 3-2	-1.938	1.268	34	-1.528	0.136
Identify known value 1-0	3.568	1.713	34	2.083	0.045

	Value	Std.Error	DF	t-value	p-value
Intercept	9.325	0.893	34	10.438	0.000
Problem 2-1	0.922	1.243	34	0.742	0.463
Problem 3-2	1.030	1.791	34	0.575	0.569
Inconsistent units 1-0	-3.927	1.846	34	-2.128	0.041

	Value	Std.Error	DF	t-value	p-value
Intercept	8.678	0.936	34	9.274	0.000
Problem 2-1	0.949	1.212	34	0.783	0.439
Problem 3-2	-2.618	1.211	34	-2.162	0.038
Using incorrectly generated information 1-0	3.078	1.286	34	2.395	0.022

	Value	Std.Error	DF	t-value	p-value
Intercept	9.390	0.892	34	10.527	0.000
Problem 2-1	0.680	1.230	34	0.553	0.584
Problem 3-2	1.283	1.837	34	0.698	0.490
Means ends analysis 1-0	-4.397	1.998	34	-2.201	0.035

Significant Effects of Problem Solving Features on Performance

	Value	Std.Error	DF	t-value	p-value
Intercept	2.956	0.878	34	3.367	0.002
Problem 2-1	0.658	0.986	34	0.668	0.509
Problem 3-2	1.561	0.998	34	1.564	0.127
Incorrectly relate variables 1-0	2.560	0.852	34	3.006	0.005

	Value	Std.Error	DF	t-value	p-value
Intercept	3.547	0.794	34	4.465	0.000
Problem 2-1	0.656	1.016	34	0.645	0.523
Problem 3-2	1.387	1.009	34	1.375	0.178
Incorrect unknown value 1-0	2.773	1.054	34	2.631	0.013

	Value	Std.Error	DF	t-value	p-value
Intercept	3.884	0.619	34	6.277	0.000
Problem 2-1	0.450	0.749	34	0.601	0.552
Problem 3-2	-0.866	0.752	34	-1.152	0.257
Using incorrectly generated information 1-0	4.423	0.842	34	5.256	0.000

Significant Effects of Problem Solving Features on Effort

	Value	Std.Error	DF	t-value	p-value
Intercept	21.002	3.457	34	6.076	0.000
Problem 2-1	-1.823	0.843	34	-2.162	0.038
Problem 3-2	-0.780	0.793	34	-0.984	0.332
Identify equation 1-0	-8.262	3.361	34	-2.458	0.019

	Value	Std.Error	DF	t-value	p-value
Intercept	12.561	0.738	34	17.022	0.000
Problem 2-1	-1.942	0.809	34	-2.401	0.022
Problem 3-2	-5.371	1.735	34	-3.095	0.004
Use conversion factor 1-0	4.827	1.589	34	3.038	0.005

	Value	Std.Error	DF	t-value	p-value
Intercept	18.441	2.723	34	6.773	0.000
Problem 2-1	-1.844	0.857	34	-2.151	0.039
Problem 3-2	-0.742	0.800	34	-0.927	0.360
Plug values in equation 1-0	-5.806	2.650	34	-2.191	0.035

	Value	Std.Error	DF	t-value	p-value
Intercept	10.063	1.430	34	7.039	0.000
Problem 2-1	-0.276	0.991	34	-0.279	0.782
Problem 3-2	-0.698	0.811	34	-0.860	0.396
Identify known value 1-0	2.716	1.254	34	2.166	0.038

	Value	Std.Error	DF	t-value	p-value
Intercept	12.679	0.736	34	17.228	0.000
Problem 2-1	0.854	1.372	34	0.622	0.538
Problem 3-2	-0.580	0.828	34	-0.700	0.489
Chunking 1-0	-3.091	1.474	34	-2.097	0.044

Significant Effects of Problem Solving Features on Frustration

	Value	Std.Error	DF	t-value	p-value
Intercept	6.404	1.055	34	6.073	0.000
Problem 2-1	0.005	0.934	34	0.005	0.996
Problem 3-2	1.116	1.030	34	1.083	0.286
Misuse governing equation 1-0	2.870	1.096	34	2.619	0.013

	Value	Std.Error	DF	t-value	p-value
Intercept	7.940	0.912	34	8.704	0.000
Problem 2-1	-1.526	0.895	34	-1.705	0.097
Problem 3-2	-0.554	0.812	34	-0.683	0.499
Incorrect calculation 1-0	4.274	1.477	34	2.894	0.007

	Value	Std.Error	DF	t-value	p-value
Intercept	8.070	0.862	34	9.361	0.000
Problem 2-1	-0.600	0.907	34	-0.661	0.513
Problem 3-2	-2.304	1.131	34	-2.038	0.049
Incorrect unit derivation 1-0	3.954	1.472	34	2.686	0.011

	Value	Std.Error	DF	t-value	p-value
Intercept	7.326	0.898	34	8.158	0.000
Problem 2-1	-0.336	0.909	34	-0.370	0.714
Problem 3-2	-1.202	0.921	34	-1.305	0.201
Using incorrectly generated information 1-0	3.011	1.124	34	2.679	0.011

	Value	Std.Error	DF	t-value	p-value
Intercept	7.958	0.870	34	9.150	0.000
Problem 2-1	-1.536	1.016	34	-1.513	0.140
Problem 3-2	-0.597	0.899	34	-0.664	0.511
Plug and chug 1-0	3.202	1.453	34	2.204	0.034

APPENDIX L

EFFECTS OF PERFORMANCE MEASURES ON MENTAL WORKLOAD MEASURES

Significant Effects of Performance Measures on Overall Mental Workload

	Value	Std.Error	DF	t-value	p-value
Intercept	51.122	3.208	34	15.938	0.000
Problem 2-1	-0.054	4.027	34	-0.013	0.989
Problem 3-2	-5.324	3.711	34	-1.435	0.161
X 2E correct representation 1-0	-10.983	3.725	34	-2.949	0.006

	Value	Std.Error	DF	t-value	p-value
Intercept	59.758	5.185	34	11.525	0.000
Problem 2-1	-2.642	3.252	34	-0.813	0.422
Problem 3-2	-0.799	3.162	34	-0.253	0.802
X4C correct equations 1-0	-16.188	5.143	34	-3.147	0.003

	Value	Std.Error	DF	t-value	p-value
Intercept	46.468	2.987	34	15.555	0.000
Problem 2-1	-5.254	3.333	34	-1.576	0.124
Problem 3-2	-7.807	3.572	34	-2.186	0.036
X5C Number of Tries to correct mechanical tasks	7.172	2.401	34	2.988	0.005

	Value	Std.Error	DF	t-value	p-value
Intercept	40.342	2.992	34	13.482	0.000
Problem 2-1	0.011	3.354	34	0.003	0.997
Problem 3-2	0.432	3.231	34	0.134	0.895
X8B Conceptual Errors	12.330	2.650	34	4.653	0.000

	Value	Std.Error	DF	t-value	p-value
Intercept	36.304	4.126	34	8.800	0.000
Problem 2-1	1.100	3.548	34	0.310	0.758
Problem 3-2	-1.970	3.146	34	-0.626	0.535
X9A Error Rate	51.850	14.919	34	3.475	0.001

	Value	Std.Error	DF	t-value	p-value
Intercept	32.319	6.199	34	5.214	0.000
Problem 2-1	-9.070	4.093	34	-2.216	0.034
Problem 3-2	-4.650	3.442	34	-1.351	0.186
X9B Time to Completion	0.706	0.270	34	2.618	0.013

Significant Effects of Performance Measures on Mental Demand

	Value	Std.Error	DF	t-value	p-value
Intercept	12.758	0.880	34	14.505	0.000
Problem 2-1	-1.402	1.113	34	-1.259	0.217
Problem 3-2	-1.317	1.027	34	-1.283	0.208
X 2E correct representation 1-0	-2.639	1.023	34	-2.579	0.014

	Value	Std.Error	DF	t-value	p-value
Intercept	10.811	0.903	34	11.978	0.000
Problem 2-1	-1.710	1.096	34	-1.560	0.128
Problem 3-2	-0.381	1.059	34	-0.360	0.721
X8B Conceptual Errors	1.737	0.816	34	2.128	0.041

Significant Effects of Performance Measures on Temporal Demand

	Value	Std.Error	DF	t-value	p-value
Intercept	10.428	0.992	34	10.510	0.000
Problem 2-1	1.608	1.381	34	1.164	0.253
Problem 3-2	-2.226	1.286	34	-1.732	0.092
X 2E correct representation 1-0	-2.664	1.153	34	-2.310	0.027

	Value	Std.Error	DF	t-value	p-value
Intercept	7.655	0.956	34	8.006	0.000
Problem 2-1	1.828	1.210	34	1.511	0.140
Problem 3-2	-0.631	1.170	34	-0.539	0.593
X8B Conceptual Errors	3.256	0.870	34	3.742	0.001

	Value	Std.Error	DF	t-value	p-value
Intercept	8.070	1.020	34	7.915	0.000
Problem 2-1	1.384	1.303	34	1.062	0.296
Problem 3-2	-2.341	1.240	34	-1.889	0.068
X8D Management Errors	0.889	0.349	34	2.547	0.016

	Value	Std.Error	DF	t-value	p-value
Intercept	6.939	1.318	34	5.263	0.000
Problem 2-1	1.923	1.304	34	1.474	0.150
Problem 3-2	-1.447	1.160	34	-1.247	0.221
X9A Error Rate	11.983	4.816	34	2.488	0.018

	Value	Std.Error	DF	t-value	p-value
Intercept	5.349	1.878	34	2.848	0.007
Problem 2-1	-0.812	1.422	34	-0.571	0.572
Problem 3-2	-2.256	1.242	34	-1.817	0.078
X9B Time to Completion	0.200	0.082	34	2.439	0.020

Significant Effects of Performance Measures on Performance

	Value	Std.Error	DF	t-value	p-value
Intercept	3.965	0.731	34	5.424	0.000
Problem 2-1	0.368	0.997	34	0.369	0.714
Problem 3-2	0.968	0.967	34	1.001	0.324
X 1C NumHits Incorrect unknown 1-0	2.801	1.184	34	2.366	0.024

	Value	Std.Error	DF	t-value	p-value
Intercept	4.235	0.685	34	6.183	0.000
Problem 2-1	-0.030	0.961	34	-0.031	0.975
Problem 3-2	0.174	0.917	34	0.190	0.851
X5G Erasing correct work	1.099	0.477	34	2.306	0.027

	Value	Std.Error	DF	t-value	p-value
Intercept	4.191	0.698	34	6.005	0.000
Problem 2-1	0.011	0.967	34	0.011	0.991
Problem 3-2	0.273	0.919	34	0.297	0.769
X6C False Alarm Rate	21.419	9.640	34	2.222	0.033

	Value	Std.Error	DF	t-value	p-value
Intercept	7.948	1.427	34	5.569	0.000
Problem 2-1	-0.328	0.946	34	-0.347	0.731
Problem 3-2	0.336	0.914	34	0.368	0.715
X8A Answer accuracy	-3.528	1.446	34	-2.439	0.020

	Value	Std.Error	DF	t-value	p-value
Intercept	3.464	0.678	34	5.113	0.000
Problem 2-1	0.641	0.916	34	0.700	0.489
Problem 3-2	1.269	0.889	34	1.428	0.163
X8B Conceptual Errors	2.531	0.619	34	4.091	0.000

	Value	Std.Error	DF	t-value	p-value
Intercept	3.217	0.666	34	4.830	0.000
Problem 2-1	0.486	0.873	34	0.557	0.581
Problem 3-2	-0.269	0.831	34	-0.323	0.748
X8D Management Errors	1.074	0.228	34	4.714	0.000

	Value	Std.Error	DF	t-value	p-value
Intercept	1.196	0.792	34	1.509	0.140
Problem 2-1	1.762	0.828	34	2.129	0.041
Problem 3-2	0.826	0.739	34	1.118	0.271
X9A Error Rate	17.773	2.876	34	6.181	0.000

	Value	Std.Error	DF	t-value	p-value
Intercept	1.339	1.347	34	0.994	0.327
Problem 2-1	-1.531	0.996	34	-1.538	0.133
Problem 3-2	-0.021	0.863	34	-0.025	0.981
X9B Time to Completion	0.173	0.059	34	2.936	0.006

Significant Effects of Performance Measures on Effort

	Value	Std.Error	DF	t-value	p-value
Intercept	13.273	0.827	33	16.057	0.000
Problem 2-1	-0.607	0.918	33	-0.661	0.513
Problem 3-2	-0.743	0.855	33	-0.870	0.391
X 2D Explicit visual 0 5	-5.958	2.122	33	-2.807	0.008
X 2D Explicit visual 1-0	-1.054	0.896	33	-1.176	0.248

	Value	Std.Error	DF	t-value	p-value
Intercept	13.714	0.796	34	17.228	0.000
Problem 2-1	-0.558	0.917	34	-0.608	0.547
Problem 3-2	-1.080	0.841	34	-1.285	0.208
X 2E correct representation 1-0	-2.447	0.895	34	-2.736	0.010

	Value	Std.Error	DF	t-value	p-value
Intercept	15.428	1.295	34	11.910	0.000
Problem 2-1	-1.172	0.836	34	-1.402	0.170
Problem 3-2	-0.278	0.814	34	-0.342	0.735
X4C correct equations 1-0	-3.310	1.301	34	-2.544	0.016

	Value	Std.Error	DF	t-value	p-value
Intercept	11.747	0.802	34	14.646	0.000
Problem 2-1	-0.829	0.865	34	-0.959	0.345
Problem 3-2	-0.147	0.833	34	-0.176	0.861
X8B Conceptual Errors	1.932	0.701	34	2.757	0.009

Significant Effects of Performance Measures on Frustration

	Value	Std.Error	DF	t-value	p-value
Intercept	9.432	0.894	34	10.547	0.000
Problem 2-1	0.524	1.031	34	0.508	0.615
Problem 3-2	-1.003	0.945	34	-1.060	0.297
X 2E correct representation 1-0	-3.514	1.005	34	-3.495	0.001

	Value	Std.Error	DF	t-value	p-value
Intercept	12.277	1.399	34	8.777	0.000
Problem 2-1	-0.327	0.810	34	-0.404	0.689
Problem 3-2	0.329	0.787	34	0.417	0.679
X4C correct equations 1-0	-5.251	1.329	34	-3.951	0.000

	Value	Std.Error	DF	t-value	p-value
Intercept	7.938	0.841	34	9.437	0.000
Problem 2-1	-1.191	0.809	34	-1.473	0.150
Problem 3-2	-2.057	0.869	34	-2.368	0.024
X5C Number of Times to correct mechanical	2.577	0.595	34	4.330	0.000

	Value	Std.Error	DF	t-value	p-value
Intercept	6.496	0.888	34	7.317	0.000
Problem 2-1	0.174	0.906	34	0.192	0.849
Problem 3-2	0.417	0.871	34	0.478	0.635
X8B Conceptual Errors	3.000	0.758	34	3.959	0.000

	Value	Std.Error	DF	t-value	p-value
Intercept	5.360	1.182	34	4.534	0.000
Problem 2-1	0.538	0.952	34	0.565	0.576
Problem 3-2	-0.135	0.844	34	-0.160	0.874
X9A Error Rate	13.389	4.203	34	3.185	0.003

Appendix M

Odds Ratios by Gender

All 3 problems collectively

	Males did	Males did not	Females' did	Females' did not	Odds Ratios Males more likely	Odds Ratios Females more likely	SE	p-value
Identify equation	43	10	13	2	0.7	1.5	0.8	0.345
Implicit equation identification	30	23	9	6	0.9	1.2	0.6	0.387
Identified assumption	1	52	1	14	0.3	3.7	1.2	0.218
Identify prior knowledge	3	50	0	15	2.1	0.5	1.5	0.353
Identify conversion factor	1	52	0	15	0.9	1.1	1.7	0.398
Use conversion factor	16	37	6	9	0.6	1.5	0.6	0.304
Draw a picture / diagram	20	33	6	9	0.9	1.1	0.6	0.394
Make a table	3	50	0	15	2.1	0.5	1.5	0.353
Relate variables	23	30	6	9	1.2	0.9	0.6	0.387
Manipulate equation	9	44	3	12	0.8	1.2	0.7	0.383
Derive units	9	44	3	12	0.8	1.2	0.7	0.383
Plug values in equation	41	12	15	0	0.1	9.3	1.5	0.126
Document math	41	12	8	7	3.0	0.3	0.6	0.074
Solve intermediate value	43	10	15	0	0.1	7.5	1.5	0.158
Identify unknown value	9	44	2	13	1.3	0.8	0.8	0.373
Identify final answer	34	19	12	3	0.4	2.2	0.7	0.193
Erase work	31	22	11	4	0.5	2.0	0.6	0.223
Abandon process / Start over	2	51	2	13	0.3	3.9	0.9	0.140
Check accuracy	2	51	1	14	0.5	1.8	1.1	0.341
Identify errors	47	6	14	1	0.6	1.8	1.0	0.332
Incorrectly relate variables	15	38	7	8	0.5	2.2	0.6	0.158

Misuse governing equation	11	42	6	9	0.4	2.5	0.6	0.122
Incorrect visual/graphic representation	1	52	0	15	0.9	1.1	1.7	0.398
Incorrect assumptions	0	53	1	14	0.1	11.1	1.7	0.140
Incorrectly manipulate equation	1	52	0	15	0.9	1.1	1.7	0.398
Incorrect calculation	6	47	4	11	0.4	2.8	0.7	0.129
Incorrect unit derivation	2	51	3	12	0.2	6.4	0.9	0.045
Incorrect known value	5	48	3	12	0.4	2.4	0.8	0.203
Incorrect unknown value	3	50	2	13	0.4	2.6	0.9	0.226
Ignored problem constraints	6	47	2	13	0.8	1.2	0.8	0.388
Irrelevant information	9	44	4	11	0.6	1.8	0.7	0.273
Inconsistent transcription	3	50	3	12	0.2	4.2	0.8	0.088
Inconsistent units	15	38	3	12	1.6	0.6	0.7	0.317
Incorrect unit assignment	4	49	1	14	1.1	0.9	1.0	0.395
Using incorrectly generated information	10	43	6	9	0.3	2.9	0.6	0.092
Missing Units Throughout	2	51	0	15	1.5	0.7	1.6	0.386
Erasing correct work	16	37	6	9	0.6	1.5	0.6	0.304
Plug and chug	12	41	7	8	0.3	3.0	0.6	0.074
Guess and Check	6	47	5	10	0.3	3.9	0.7	0.051
Segmentation	17	36	4	11	1.3	0.8	0.6	0.366
Means-ends analysis	9	44	0	15	6.6	0.2	1.5	0.177
Chunking	16	37	1	14	6.1	0.2	0.9	0.056
Forward chaining	7	46	2	13	1.0	1.0	0.8	0.399
Correct Answer	34	19	2	13	11.6	0.1	0.7	0.002
Correct but Incorrect Units	4	49	1	14	1.1	0.9	1.0	0.395
Incorrect Answer	32	21	12	3	0.4	2.6	0.7	0.139

Appendix N

Odds Ratios by Ethnicity

All 3 problems collectively

	Caucasian students' did	Caucasian students' did not	Minority student' did	Minority students' did not	Odds Ratios Caucasian students' were more likely	Odds Ratios Minority students' were more likely	SE	p-value
Identify equation	48	10	6	2	1.60	0.63	0.8	0.338
Implicit equation identification	32	26	6	2	0.41	2.44	0.8	0.211
Identified assumption	2	56	0	8	0.75	1.33	1.6	0.393
Identify prior knowledge	2	56	0	8	0.75	1.33	1.6	0.393
Identify conversion factor	1	57	0	8	0.44	2.25	1.7	0.355
Use conversion factor	17	41	3	5	0.69	1.45	0.7	0.352
Draw a picture / diagram	21	37	3	5	0.95	1.06	0.7	0.398
Make a table	3	55	0	8	1.07	0.93	1.6	0.399
Relate variables	24	34	3	5	1.18	0.85	0.7	0.389
Manipulate equation	10	48	1	7	1.46	0.69	1.0	0.369
Derive units	10	48	1	7	1.46	0.69	1.0	0.369
Plug values in equation	48	10	6	2	1.60	0.63	0.8	0.338
Document math	42	16	5	3	1.58	0.63	0.7	0.331
Solve intermediate value	48	10	8	0	0.27	3.68	1.5	0.273
Identify unknown value	10	48	1	7	1.46	0.69	1.0	0.369
Identify final answer	40	18	4	4	2.22	0.45	0.7	0.217
Erase work	35	23	6	2	0.51	1.97	0.8	0.276
Abandon process / Start over	4	54	0	8	1.40	0.71	1.5	0.389
Check accuracy	3	55	0	8	1.07	0.93	1.6	0.399
Identify errors	52	6	8	0	0.48	2.10	1.5	0.354
Incorrectly relate variables	20	38	2	6	1.58	0.63	0.8	0.338

Misuse governing equation	15	43	2	6	1.05	0.96	0.8	0.398
Incorrect visual/graphic representation	1	57	0	8	0.44	2.25	1.7	0.355
Incorrect assumptions	1	57	0	8	0.44	2.25	1.7	0.355
Incorrectly manipulate equation	1	57	0	8	0.44	2.25	1.7	0.355
Incorrect calculation	8	50	2	6	0.48	2.08	0.8	0.270
Incorrect unit derivation	4	54	1	7	0.52	1.93	1.0	0.324
Incorrect known value	6	52	2	6	0.35	2.89	0.9	0.184
Incorrect unknown value	5	53	0	8	1.75	0.57	1.5	0.373
Ignored problem constraints	7	51	0	8	2.48	0.40	1.5	0.333
Irrelevant information	10	48	2	6	0.63	1.60	0.8	0.338
Inconsistent transcription	5	53	1	7	0.66	1.51	1.0	0.366
Inconsistent units	16	42	2	6	1.14	0.88	0.8	0.393
Incorrect unit assignment	3	55	2	6	0.16	6.11	0.9	0.059
Using incorrectly generated information	13	45	2	6	0.87	1.15	0.8	0.393
Missing Units Throughout	0	58	2	6	0.02	45.00	1.6	0.024
Erasing correct work	18	40	3	5	0.75	1.33	0.7	0.370
Plug and chug	17	41	2	6	1.24	0.80	0.8	0.384
Guess and Check	9	49	1	7	1.29	0.78	1.0	0.386
Segmentation	18	40	3	5	0.75	1.33	0.7	0.370
Means-ends analysis	7	51	2	6	0.41	2.43	0.8	0.229
Chunking	14	44	2	6	0.95	1.05	0.8	0.398
Forward chaining	7	51	1	7	0.96	1.04	1.0	0.399
Correct Answer	30	28	4	4	1.07	0.93	0.7	0.397
Correct but Incorrect Units	3	55	2	6	0.16	6.11	0.9	0.059
Incorrect Answer	39	19	4	4	2.05	0.49	0.7	0.243

Appendix O

Odds Ratios by Pre-engineering Experience

All 3 problems collectively

	Students with pre-engineering experience did	Students with pre-engineering experience did not	Students without pre-engineering experience did	Students without pre-engineering experience did not	Odds Ratios: Students with pre-engineering were more likely	Odds Ratios: Students without pre-engineering were more likely	SE	p-value
Identify equation	13	4	43	8	0.60	1.65	0.7	0.299
Implicit equation identification	10	7	29	22	1.08	0.92	0.6	0.395
Identified assumption	1	16	1	50	3.13	0.32	1.2	0.252
Identify prior knowledge	2	15	1	50	6.67	0.15	1.1	0.084
Identify conversion factor	0	17	1	50	0.96	1.04	1.7	0.399
Use conversion factor	5	12	17	34	0.83	1.20	0.6	0.380
Draw a picture / diagram	5	12	21	30	0.60	1.68	0.6	0.269
Make a table	0	17	3	48	0.40	2.53	1.5	0.333
Relate variables	6	11	23	28	0.66	1.51	0.6	0.307
Manipulate equation	3	14	9	42	1.00	1.00	0.7	0.399
Derive units	3	14	9	42	1.00	1.00	0.7	0.399
Plug values in equation	12	5	44	7	0.38	2.62	0.6	0.131
Document math	16	1	33	18	8.73	0.11	0.9	0.022
Solve intermediate value	14	3	44	7	0.74	1.35	0.7	0.366
Identify unknown value	1	16	10	41	0.26	3.90	0.9	0.133
Identify final answer	15	2	31	20	4.84	0.21	0.7	0.041
Erase work	8	9	34	17	0.44	2.25	0.6	0.138
Abandon process / Start over	0	17	4	47	0.30	3.32	1.5	0.292

Check accuracy	0	17	3	48	0.40	2.53	1.5	0.333
Identify errors	14	3	47	4	0.40	2.52	0.8	0.196
Incorrectly relate variables	4	13	18	33	0.56	1.77	0.6	0.259
Misuse governing equation	3	14	14	37	0.57	1.77	0.7	0.279
Incorrect visual/graphic representation	0	17	1	50	0.96	1.04	1.7	0.399
Incorrect assumptions	0	17	1	50	0.96	1.04	1.7	0.399
Incorrectly manipulate equation	1	16	0	51	9.36	0.11	1.7	0.160
Incorrect calculation	2	15	8	43	0.72	1.40	0.8	0.364
Incorrect unit derivation	0	17	5	46	0.24	4.14	1.5	0.255
Incorrect known value	2	15	6	45	1.00	1.00	0.8	0.399
Incorrect unknown value	2	15	3	48	2.13	0.47	0.9	0.275
Ignored problem constraints	4	13	4	47	3.62	0.28	0.7	0.086
Irrelevant information	4	13	9	42	1.44	0.70	0.7	0.342
Inconsistent transcription	1	16	5	46	0.58	1.74	1.0	0.338
Inconsistent units	4	13	14	37	0.81	1.23	0.6	0.378
Incorrect unit assignment	0	17	5	46	0.24	4.14	1.5	0.255
Using incorrectly generated information	4	13	12	39	1.00	1.00	0.6	0.399
Missing Units Throughout	0	17	2	49	0.57	1.77	1.6	0.374
Erasing correct work	5	12	17	34	0.83	1.20	0.6	0.380
Plug and chug	4	13	15	36	0.74	1.35	0.6	0.354
Guess and Check	2	15	9	42	0.62	1.61	0.8	0.330
Segmentation	4	13	17	34	0.62	1.63	0.6	0.293
Means-ends analysis	2	15	7	44	0.84	1.19	0.8	0.389
Chunking	6	11	11	40	1.98	0.50	0.6	0.205
Forward chaining	3	14	6	45	1.61	0.62	0.7	0.323
Correct Answer	12	5	24	27	2.70	0.37	0.6	0.093
Correct but Incorrect Units	1	16	4	47	0.73	1.36	1.0	0.380
Incorrect Answer	10	7	34	17	0.71	1.40	0.6	0.333

Appendix P

Odds Ratios by Calculus Experience

All 3 problems collectively

	Students with calculus did	Students with calculus did not	Students without calculus did	Students without calculus did not	Odds Ratios: Students with calculus were more likely	Odds Ratios: Students without calculus were more likely	SE	p-value
Identify equation	42	9	14	3	1.00	1.00	0.7	0.399
Implicit equation identification	28	23	11	6	0.66	1.51	0.6	0.307
Identified assumption	1	50	1	16	0.32	3.13	1.2	0.252
Identify prior knowledge	3	48	0	17	2.53	0.40	1.5	0.333
Identify conversion factor	1	50	0	17	1.04	0.96	1.7	0.399
Use conversion factor	17	34	5	12	1.20	0.83	0.6	0.380
Draw a picture / diagram	17	34	9	8	0.44	2.25	0.6	0.138
Make a table	3	48	0	17	2.53	0.40	1.5	0.333
Relate variables	20	31	9	8	0.57	1.74	0.6	0.240
Manipulate equation	11	40	1	16	4.40	0.23	0.9	0.108
Derive units	9	42	3	14	1.00	1.00	0.7	0.399
Plug values in equation	42	9	14	3	1.00	1.00	0.7	0.399
Document math	37	14	12	5	1.10	0.91	0.6	0.394
Solve intermediate value	41	10	17	0	0.11	8.86	1.5	0.134
Identify unknown value	7	44	4	13	0.52	1.93	0.7	0.247
Identify final answer	36	15	10	7	1.68	0.60	0.6	0.262
Erase work	30	21	12	5	0.60	1.68	0.6	0.269
Abandon process / Start over	2	49	2	15	0.31	3.27	0.9	0.181
Check accuracy	2	49	1	16	0.65	1.53	1.1	0.369

Identify errors	45	6	16	1	0.47	2.13	1.0	0.290
Incorrectly relate variables	14	37	8	9	0.43	2.35	0.6	0.127
Misuse governing equation	10	41	7	10	0.35	2.87	0.6	0.081
Incorrect visual/graphic	1	50	0	17	1.04	0.96	1.7	0.399
Incorrect assumptions	0	51	1	16	0.11	9.36	1.7	0.160
Incorrectly manipulate equation	1	50	0	17	1.04	0.96	1.7	0.399
Incorrect calculation	7	44	3	14	0.74	1.35	0.7	0.366
Incorrect unit derivation	2	49	3	14	0.19	5.25	0.9	0.068
Incorrect known value	4	47	4	13	0.28	3.62	0.7	0.086
Incorrect unknown value	4	47	1	16	1.36	0.73	1.0	0.380
Ignored problem constraints	6	45	2	15	1.00	1.00	0.8	0.399
Irrelevant information	9	42	4	13	0.70	1.44	0.7	0.342
Inconsistent transcription	4	47	2	15	0.64	1.57	0.8	0.346
Inconsistent units	14	37	4	13	1.23	0.81	0.6	0.378
Incorrect unit assignment	2	49	3	14	0.19	5.25	0.9	0.068
Using incorrectly generated information	9	42	7	10	0.31	3.27	0.6	0.056
Missing Units Throughout	0	51	2	15	0.06	16.61	1.6	0.081
Erasing correct work	16	35	6	11	0.84	1.19	0.6	0.381
Plug and chug	15	36	4	13	1.35	0.74	0.6	0.354
Guess and Check	7	44	4	13	0.52	1.93	0.7	0.247
Segmentation	15	36	6	11	0.76	1.31	0.6	0.358
Means-ends analysis	7	44	2	15	1.19	0.84	0.8	0.389
Chunking	15	36	2	15	3.13	0.32	0.7	0.124
Forward chaining	6	45	3	14	0.62	1.61	0.7	0.323
Correct Answer	31	20	5	12	3.72	0.27	0.6	0.032
Correct but Incorrect Units	2	49	3	14	0.19	5.25	0.9	0.068
Incorrect Answer	33	18	11	6	1.00	1.00	0.6	0.399

APPENDIX Q

SIGNIFICANT EFFECTS ON PROBLEM SOLVING FEATURES FROM LINEAR MIXED EFFECTS MODELS OF ALL PARTICIPANT FACTORS COLLECTIVELY

Manipulate.equation	Value	Std.Error	DF	t-value	p-value
Intercept	-4.657	1.780	39	-2.610	0.013
Problem 2-1	3.716	0.790	39	4.675	0.000
Problem 3-2	-26.239	177158	39	0.000	1.000
Males-Females	-1.945	1.460	22	-1.331	0.197
Caucasians - Other	-0.533	1.480	22	-0.360	0.722
Calculus-Precalculus	3.549	1.630	22	2.180	0.040
Preengineering experience-None	0.025	1.190	22	0.021	0.984

Identify.final.answer	Value	Std.Error	DF	t-value	p-value
Intercept	4.395	2.378	39	1.849	0.072
Problem 2-1	-1.829	0.742	39	-2.466	0.018
Problem 3-2	-2.698	0.761	39	-3.546	0.001
Males-Females	-3.837	2.107	22	-1.821	0.082
Caucasians - Other	-1.600	2.189	22	-0.731	0.473
Calculus-Precalculus	2.837	1.986	22	1.428	0.167
Preengineering experience-None	2.686	1.149	22	2.337	0.029

Incorrect.unit.derivation	Value	Std.Error	DF	t-value	p-value
Intercept	-40.404	4.928	39	-8.199	0.000
Problem 2-1	-0.136	0.029	39	-4.711	0.000
Problem 3-2	63.710	0.152	39	419.416	0.000
Males-Females	-26.610	4.496	22	-5.918	0.000
Caucasians - Other	-19.408	4.507	22	-4.306	0.000
Calculus-Precalculus	14.397	4.213	22	3.417	0.003
Preengineering experience-None	-37.932	3.735	22	-10.156	0.000

Incorrect.unknown.value	Value	Std.Error	DF	t-value	p-value
Intercept	-3.16E+14	1.89E+14	39	-1.670	0.103
Problem 2-1	0	1.01E+07	39	0.000	1.000
Problem 3-2	-1.59E+14	1.34E+14	39	-1.184	0.243
Males-Females	-3.77E+15	1.08E+14	22	-34.932	0.000
Caucasians - Other	3.16E+14	1.89E+14	22	1.670	0.109
Calculus-Precalculus	2	1.57E+07	22	0.000	1.000
Preengineering experience-None	3.77E+15	1.08E+14	22	34.932	0.000

Ignored.problem.constraints	Value	Std.Error	DF	t-value	p-value
Intercept	-45.925	6.193	39	-7.415	0.000
Problem 2-1	40.690	0.007	39	5588.513	0.000
Problem 3-2	0.243	0.010	39	25.245	0.000
Males-Females	-2.371	5.651	22	-0.420	0.679
Caucasians - Other	7.587	5.663	22	1.340	0.194
Calculus-Precalculus	-5.351	5.289	22	-1.012	0.323
Preengineering experience-None	13.574	4.687	22	2.896	0.008

Plug.and.chug	Value	Std.Error	DF	t-value	p-value
Intercept	-2.620	1.369	39	-1.913	0.063
Problem 2-1	2.729	0.983	39	2.776	0.008
Problem 3-2	1.963	0.996	39	1.971	0.056
Males-Females	-2.354	1.131	22	-2.082	0.049
Caucasians - Other	0.465	1.117	22	0.417	0.681
Calculus-Precalculus	1.763	1.170	22	1.507	0.146
Preengineering experience-None	-0.174	0.788	22	-0.221	0.827

Means.ends.analysis	Value	Std.Error	DF	t-value	p-value
Intercept	-103.712	5.860	39	-17.698	0.000
Problem 2-1	6.832	0.299	39	22.811	0.000
Problem 3-2	65.298	0.298	39	218.802	0.000
Males-Females	63.837	5.345	22	11.944	0.000
Caucasians - Other	12.851	5.354	22	2.400	0.025
Calculus-Precalculus	-37.293	5.000	22	-7.458	0.000
Preengineering experience-None	-4.877	4.424	22	-1.102	0.282

Appendix R

Significant Effects on Performance from Linear Mixed Effects Models of all Participant Factors

2A.Explicit.definition	Value	Std.Error	DF	t-value	p-value
Intercept	-22.738	4.385	39	-5.185	0.000
Problem 2-1	-38.465	0.007	39	-5361.031	0.000
Problem 3-2	-39.231	0.006	39	-6992.986	0.000
Males-Females	-19.618	3.990	22	-4.916	0.000
Caucasians - Other	15.411	4.021	22	3.833	0.001
Calculus-Precalculus	-2.349	3.738	22	-0.628	0.536
Preengineering experience-None	21.971	3.313	22	6.632	0.000

2B.Correct.definition	Value	Std.Error	DF	t-value	p-value
Intercept	48.015	6.039	39	7.950	0.000
Problem 2-1	-40.306	0.001	39	-60070.860	0.000
Problem 3-2	-0.005	0.001	39	-5.640	0.000
Males-Females	1.239	5.510	22	0.220	0.824
Caucasians - Other	-4.848	5.521	22	-0.880	0.390
Calculus-Precalculus	3.450	5.157	22	0.670	0.511
Preengineering experience-None	-15.633	4.570	22	-3.420	0.002

3.Strategy	Value	Std.Error	DF	t-value	p-value
Intercept	0.294	0.131	39	2.243	0.031
Problem 2-1	-0.024	0.091	39	-0.262	0.795
Problem 3-2	-0.112	0.091	39	-1.235	0.224
Males-Females	0.331	0.110	22	3.018	0.006
Caucasians - Other	-0.025	0.115	22	-0.213	0.833
Calculus-Precalculus	-0.105	0.110	22	-0.955	0.350
Preengineering experience-None	0.130	0.091	22	1.431	0.167

4B.correct.knowns	Value	Std.Error	DF	t-value	p-value
Intercept	-41.571	3.669	39	-11.329	0.000
Problem 2-1	60.658	0.070	39	870.234	0.000
Problem 3-2	41.606	0.027	39	1526.139	0.000
Males-Females	40.024	3.350	22	11.947	0.000
Caucasians - Other	48.886	3.365	22	14.526	0.000
Calculus-Precalculus	13.628	3.148	22	4.330	0.000
Preengineering experience-None	-19.577	2.803	22	-6.984	0.000

7B.Indicate.Answer	Value	Std.Error	DF	t-value	p-value
Intercept	4.395	2.378	39	1.849	0.072
Problem 2-1	-1.829	0.742	39	-2.466	0.018
Problem 3-2	-2.698	0.761	39	-3.546	0.001
Males-Females	-3.837	2.107	22	-1.821	0.082
Caucasians - Other	-1.600	2.189	22	-0.731	0.473
Calculus-Precalculus	2.837	1.986	22	1.428	0.167
Preengineering experience-None	2.686	1.149	22	2.337	0.029

8A.Answer.accuracy	Value	Std.Error	DF	t-value	p-value
Intercept	0.263	0.176	39	1.496	0.143
Problem 2-1	-0.021	0.122	39	-0.168	0.867
Problem 3-2	0.010	0.121	39	0.082	0.935
Males-Females	0.360	0.147	22	2.444	0.023
Caucasians - Other	-0.153	0.154	22	-0.991	0.333
Calculus-Precalculus	0.055	0.148	22	0.370	0.715
Preengineering experience-None	0.081	0.122	22	0.666	0.512

9B.Time.to.Completion	Value	Std.Error	DF	t-value	p-value
Intercept	26.218	3.403	39	7.704	0.000
Problem 2-1	1.847	1.843	39	1.003	0.322
Problem 3-2	-3.899	1.846	39	-2.112	0.041
Males-Females	0.062	2.966	22	0.021	0.984
Caucasians - Other	-7.972	3.039	22	-2.623	0.016
Calculus-Precalculus	-3.855	2.912	22	-1.324	0.199
Preengineering experience-None	-1.229	2.464	22	-0.499	0.623

Appendix S

Significant Relationships between Process and Outcome Measures from Linear Mixed Effects Models

X8A.Answer.accuracy

	Value	Std.Error	DF	t-value	p-value
Intercept	0.429	0.064	78	6.691	0.000
Problem 2-1	-0.033	0.068	78	-0.488	0.627
Problem 3-2	0.010	0.066	78	0.158	0.875
Semester Spring 2011-Fall 2009	0.384	0.069	61	5.548	0.000
X2E.correct.representation	0.141	0.062	78	2.284	0.025

X8A.Answer.accuracy

	Value	Std.Error	DF	t-value	p-value
Intercept	0.230	0.070	78	3.278	0.002
Problem 2-1	0.017	0.066	78	0.263	0.793
Problem 3-2	0.022	0.065	78	0.336	0.738
Semester Spring 2011-Fall 2009	0.407	0.057	61	7.112	0.000
X3.Strategy	0.514	0.095	78	5.425	0.000

X8A.Answer.accuracy

	Value	Std.Error	DF	t-value	p-value
Intercept	0.424	0.065	78	6.556	0.000
Problem 2-1	0.001	0.066	78	0.016	0.987
Problem 3-2	0.049	0.065	78	0.752	0.454
Semester Spring 2011-Fall 2009	0.406	0.071	61	5.741	0.000
X4D.NumHitKnowns	0.230	0.085	78	2.698	0.009

X8A.Answer.accuracy

	Value	Std.Error	DF	t-value	p-value
Intercept	0.191	0.122	78	1.563	0.122
Problem 2-1	0.019	0.068	78	0.283	0.778
Problem 3-2	0.047	0.067	78	0.699	0.487
Semester Spring 2011-Fall 2009	0.383	0.067	61	5.669	0.000
X5B.correct.mechanical	0.288	0.111	78	2.586	0.012

X8A.Answer.accuracy

	Value	Std.Error	DF	t-value	p-value
Intercept	-0.401	0.141	78	-2.848	0.006
Problem 2-1	0.045	0.060	78	0.747	0.457
Problem 3-2	0.052	0.059	78	0.888	0.378
Semester Spring 2011-Fall 2009	0.322	0.062	61	5.196	0.000
X6A.Sensitivity	1.054	0.158	78	6.666	0.000

X8A.Answer.accuracy

	Value	Std.Error	DF	t-value	p-value
Intercept	0.155	0.066	78	2.343	0.022
Problem 2-1	0.071	0.058	78	1.230	0.222
Problem 3-2	0.060	0.056	78	1.075	0.286
Semester Spring 2011-Fall 2009	0.307	0.060	61	5.144	0.000
X6B.Hit.Rate	0.563	0.072	78	7.843	0.000

X8B.Conceptual.Errors

	Value	Std.Error	DF	t-value	p-value
Intercept	0.819	0.100	78	8.177	0.000
Problem 2-1	-0.347	0.120	78	-2.901	0.005
Problem 3-2	-0.514	0.116	78	-4.422	0.000
Semester Spring 2011-Fall 2009	-0.103	0.100	61	-1.026	0.309
X2E.correct.representation	-0.351	0.102	78	-3.452	0.001

X8B.Conceptual.Errors

	Value	Std.Error	DF	t-value	p-value
Intercept	1.240	0.179	78	6.944	0.000
Problem 2-1	-0.347	0.118	78	-2.938	0.004
Problem 3-2	-0.464	0.117	78	-3.970	0.000
Semester Spring 2011-Fall 2009	-0.208	0.104	61	-2.008	0.049
X4B.correct.knowns	-0.577	0.170	78	-3.390	0.001

X8B.Conceptual.Errors

	Value	Std.Error	DF	t-value	p-value
Intercept	1.768	0.156	78	11.359	0.000
Problem 2-1	-0.480	0.104	78	-4.608	0.000
Problem 3-2	-0.486	0.102	78	-4.763	0.000
Semester Spring 2011-Fall 2009	-0.177	0.084	61	-2.098	0.040
X4C.correct.equations	-1.128	0.144	78	-7.837	0.000

X8B.Conceptual.Errors

	Value	Std.Error	DF	t-value	p-value
Intercept	1.554	0.262	78	5.942	0.000
Problem 2-1	-0.467	0.121	78	-3.865	0.000
Problem 3-2	-0.580	0.118	78	-4.932	0.000
Semester Spring 2011-Fall 2009	-0.072	0.101	61	-0.720	0.475
X6A.Sensitivity	-0.995	0.297	78	-3.349	0.001

X8B.Conceptual.Errors

	Value	Std.Error	DF	t-value	p-value
Intercept	1.093	0.119	78	9.190	0.000
Problem 2-1	-0.507	0.117	78	-4.333	0.000
Problem 3-2	-0.595	0.113	78	-5.248	0.000
Semester Spring 2011-Fall 2009	-0.034	0.097	61	-0.352	0.726
X6B.Hit.Rate	-0.653	0.136	78	-4.782	0.000

X8C.Mechanical.Errors

	Value	Std.Error	DF	t-value	p-value
Intercept	1.174	0.037	78	31.436	0.000
Problem 2-1	0.006	0.022	78	0.269	0.788
Problem 3-2	0.005	0.022	78	0.226	0.822
Semester Spring 2011-Fall 2009	0.013	0.019	61	0.695	0.490
X5B.correct.mechanical	-1.184	0.035	78	-34.072	0.000

X8C.Mechanical.Errors

	Value	Std.Error	DF	t-value	p-value
Intercept	0.149	0.069	78	2.156	0.034
Problem 2-1	0.090	0.068	78	1.332	0.187
Problem 3-2	0.095	0.066	78	1.439	0.154
Semester Spring 2011-Fall 2009	-0.051	0.056	61	-0.907	0.368
X6B.Hit.Rate	-0.161	0.079	78	-2.028	0.046

X8D.Management.Errors

	Value	Std.Error	DF	t-value	p-value
Intercept	3.878	0.552	78	7.022	0.000
Problem 2-1	-0.905	0.295	78	-3.067	0.003
Problem 3-2	-0.030	0.270	78	-0.111	0.912
Semester Spring 2011-Fall 2009	0.162	0.240	61	0.677	0.501
X2B.Correct.definition	-2.486	0.513	78	-4.844	0.000

X8D.Management.Errors

	Value	Std.Error	DF	t-value	p-value
Intercept	2.002	0.305	78	6.556	0.000
Problem 2-1	-0.472	0.296	78	-1.590	0.116
Problem 3-2	-0.034	0.289	78	-0.117	0.907
Semester Spring 2011-Fall 2009	0.058	0.240	61	0.242	0.809
X3.Strategy	-1.201	0.416	78	-2.887	0.005

X8D.Management.Errors

	Value	Std.Error	DF	t-value	p-value
Intercept	2.675	0.434	78	6.165	0.000
Problem 2-1	-0.256	0.297	78	-0.862	0.391
Problem 3-2	0.167	0.293	78	0.569	0.571
Semester Spring 2011-Fall 2009	-0.092	0.242	61	-0.379	0.706
X4B.correct.knowns	-1.399	0.416	78	-3.359	0.001

X8D.Management.Errors

	Value	Std.Error	DF	t-value	p-value
Intercept	0.711	0.408	78	1.741	0.086
Problem 2-1	-0.607	0.311	78	-1.950	0.055
Problem 3-2	-0.555	0.373	78	-1.487	0.141
Semester Spring 2011-Fall 2009	-0.141	0.258	61	-0.549	0.585
X5A.execute.task	0.317	0.140	78	2.256	0.027

X8D.Management.Errors

	Value	Std.Error	DF	t-value	p-value
Intercept	2.840	0.361	78	7.859	0.000
Problem 2-1	-0.425	0.280	78	-1.519	0.133
Problem 3-2	-0.755	0.310	78	-2.432	0.017
Semester Spring 2011-Fall 2009	0.095	0.230	61	0.410	0.683
X5D.correct.management	-1.532	0.310	78	-4.942	0.000

X8D.Management.Errors

	Value	Std.Error	DF	t-value	p-value
Intercept	0.691	0.306	78	2.260	0.027
Problem 2-1	-0.730	0.301	78	-2.427	0.018
Problem 3-2	0.035	0.284	78	0.124	0.902
Semester Spring 2011-Fall 2009	-0.448	0.268	61	-1.670	0.100
X5F.Number.of.tasks	0.048	0.013	78	3.869	0.000

X8D.Management.Errors

	Value	Std.Error	DF	t-value	p-value
Intercept	0.650	0.196	78	3.310	0.001
Problem 2-1	-0.095	0.227	78	-0.421	0.675
Problem 3-2	0.320	0.222	78	1.438	0.155
Semester Spring 2011-Fall 2009	0.109	0.183	61	0.597	0.553
X5G.Erasing.correct.work	1.209	0.112	78	10.775	0.000

X8D.Management.Errors

	Value	Std.Error	DF	t-value	p-value
Intercept	3.696	0.634	78	5.831	0.000
Problem 2-1	-0.545	0.286	78	-1.902	0.061
Problem 3-2	-0.103	0.279	78	-0.369	0.713
Semester Spring 2011-Fall 2009	0.274	0.252	61	1.084	0.283
X6A.Sensitivity	-2.747	0.718	78	-3.825	0.000

X8D.Management.Errors

	Value	Std.Error	DF	t-value	p-value
Intercept	2.350	0.293	78	8.009	0.000
Problem 2-1	-0.635	0.276	78	-2.301	0.024
Problem 3-2	-0.133	0.267	78	-0.500	0.619
Semester Spring 2011-Fall 2009	0.348	0.250	61	1.389	0.170
X6B.Hit.Rate	-1.665	0.331	78	-5.034	0.000

X8D.Management.Errors

	Value	Std.Error	DF	t-value	p-value
Intercept	0.602	0.226	78	2.664	0.009
Problem 2-1	0.067	0.256	78	0.261	0.795
Problem 3-2	0.431	0.250	78	1.725	0.089
Semester Spring 2011-Fall 2009	0.178	0.203	61	0.877	0.384
X6C.False.Alarm.Rate	18.711	2.254	78	8.300	0.000

X9A.Error.Rate

	Value	Std.Error	DF	t-value	p-value
Intercept	0.226	0.026	78	8.566	0.000
Problem 2-1	-0.018	0.025	78	-0.727	0.469
Problem 3-2	0.005	0.026	78	0.192	0.848
Semester Spring 2011-Fall 2009	-0.088	0.027	61	-3.229	0.002
X2F.NumRepHits	0.044	0.015	78	2.986	0.004

X9A.Error.Rate

	Value	Std.Error	DF	t-value	p-value
Intercept	0.383	0.040	78	9.608	0.000
Problem 2-1	-0.053	0.023	78	-2.255	0.027
Problem 3-2	-0.024	0.023	78	-1.048	0.298
Semester Spring 2011-Fall 2009	-0.082	0.026	61	-3.108	0.003
X4C.correct.equations	-0.133	0.035	78	-3.743	0.000

X9A.Error.Rate

	Value	Std.Error	DF	t-value	p-value
Intercept	0.358	0.045	78	7.956	0.000
Problem 2-1	-0.054	0.024	78	-2.225	0.029
Problem 3-2	-0.040	0.024	78	-1.658	0.101
Semester Spring 2011-Fall 2009	-0.071	0.027	61	-2.663	0.010
X5B.correct.mechanical	-0.102	0.041	78	-2.512	0.014

X9A.Error.Rate

	Value	Std.Error	DF	t-value	p-value
Intercept	0.264	0.024	78	10.987	0.000
Problem 2-1	-0.050	0.024	78	-2.116	0.038
Problem 3-2	-0.049	0.024	78	-2.013	0.048
Semester Spring 2011-Fall 2009	-0.088	0.028	61	-3.174	0.002
X5C.Number.of.Times. to.correct.mechanical	0.046	0.019	78	2.459	0.016

X9A.Error.Rate

	Value	Std.Error	DF	t-value	p-value
Intercept	0.343	0.035	78	9.871	0.000
Problem 2-1	-0.043	0.023	78	-1.887	0.063
Problem 3-2	-0.073	0.026	78	-2.823	0.006
Semester Spring 2011-Fall 2009	-0.076	0.028	61	-2.696	0.009
X5D.correct.management	-0.091	0.027	78	-3.307	0.001

X9A.Error.Rate

	Value	Std.Error	DF	t-value	p-value
Intercept	0.261	0.024	78	10.899	0.000
Problem 2-1	-0.046	0.024	78	-1.972	0.052
Problem 3-2	-0.059	0.026	78	-2.303	0.024
Semester Spring 2011-Fall 2009	-0.082	0.027	61	-3.007	0.004
X5E.Number.of.Times. to.correct.management	0.047	0.018	78	2.581	0.012

X9A.Error.Rate

	Value	Std.Error	DF	t-value	p-value
Intercept	0.227	0.025	78	9.137	0.000
Problem 2-1	-0.006	0.025	78	-0.228	0.820
Problem 3-2	0.003	0.024	78	0.120	0.905
Semester Spring 2011-Fall 2009	-0.090	0.027	61	-3.367	0.001
X5H.Irrelevant.Info	0.054	0.014	78	3.917	0.000

X9A.Error.Rate

	Value	Std.Error	DF	t-value	p-value
Intercept	0.463	0.056	78	8.250	0.000
Problem 2-1	-0.055	0.022	78	-2.424	0.018
Problem 3-2	-0.036	0.022	78	-1.660	0.101
Semester Spring 2011-Fall 2009	-0.060	0.028	61	-2.147	0.036
X6A.Sensitivity	-0.246	0.062	78	-3.979	0.000

X9A.Error.Rate

	Value	Std.Error	DF	t-value	p-value
Intercept	0.344	0.028	78	12.341	0.000
Problem 2-1	-0.063	0.022	78	-2.916	0.005
Problem 3-2	-0.039	0.021	78	-1.877	0.064
Semester Spring 2011-Fall 2009	-0.054	0.027	61	-1.987	0.052
X6B.Hit.Rate	-0.150	0.028	78	-5.327	0.000

X9B.Time.to.Completion

	Value	Std.Error	DF	t-value	p-value
Intercept	9.168	2.426	78	3.780	0.000
Problem 2-1	4.715	1.253	78	3.762	0.000
Problem 3-2	-1.113	1.259	78	-0.885	0.379
Semester Spring 2011-Fall 2009	8.434	1.502	61	5.616	0.000
X1B.Correct.unknown	5.566	2.250	78	2.474	0.016

X9B.Time.to.Completion

	Value	Std.Error	DF	t-value	p-value
Intercept	22.679	2.696	78	8.412	0.000
Problem 2-1	3.064	1.305	78	2.347	0.022
Problem 3-2	-0.394	1.181	78	-0.333	0.740
Semester Spring 2011-Fall 2009	8.515	1.505	61	5.657	0.000
X2B.Correct.definition	-8.611	2.418	78	-3.561	0.001

X9B.Time.to.Completion

	Value	Std.Error	DF	t-value	p-value
Intercept	13.360	1.351	78	9.887	0.000
Problem 2-1	4.593	1.273	78	3.607	0.001
Problem 3-2	-0.546	1.242	78	-0.440	0.661
Semester Spring 2011-Fall 2009	7.802	1.487	61	5.246	0.000
X2D.Explicit.visual	2.701	1.217	78	2.220	0.029

X9B.Time.to.Completion

	Value	Std.Error	DF	t-value	p-value
Intercept	12.598	1.434	78	8.787	0.000
Problem 2-1	6.022	1.343	78	4.486	0.000
Problem 3-2	1.224	1.388	78	0.882	0.380
Semester Spring 2011-Fall 2009	7.685	1.479	61	5.195	0.000
X2F.NumRepHits	2.060	0.803	78	2.564	0.012

X9B.Time.to.Completion

	Value	Std.Error	DF	t-value	p-value
Intercept	10.845	2.074	78	5.230	0.000
Problem 2-1	5.534	1.340	78	4.130	0.000
Problem 3-2	-0.659	1.278	78	-0.516	0.608
Semester Spring 2011-Fall 2009	7.011	1.527	61	4.591	0.000
X4A.Explicit.info	4.728	2.296	78	2.059	0.043

X9B.Time.to.Completion

	Value	Std.Error	DF	t-value	p-value
Intercept	9.364	1.993	78	4.698	0.000
Problem 2-1	3.541	1.329	78	2.664	0.009
Problem 3-2	-3.820	1.645	78	-2.322	0.023
Semester Spring 2011-Fall 2009	6.832	1.485	61	4.601	0.000
X5A.execute.task	2.089	0.664	78	3.144	0.002

X9B.Time.to.Completion

	Value	Std.Error	DF	t-value	p-value
Intercept	7.542	1.399	78	5.390	0.000
Problem 2-1	2.365	1.100	78	2.150	0.035
Problem 3-2	0.300	1.035	78	0.289	0.773
Semester Spring 2011-Fall 2009	3.673	1.407	61	2.612	0.011
X5F.Number.of.tasks	0.419	0.053	78	7.890	0.000

X9B.Time.to.Completion

	Value	Std.Error	DF	t-value	p-value
Intercept	12.507	1.354	78	9.240	0.000
Problem 2-1	5.485	1.243	78	4.411	0.000
Problem 3-2	0.319	1.220	78	0.262	0.794
Semester Spring 2011-Fall 2009	8.356	1.453	61	5.749	0.000
X5G.Erasing.correct.work	2.496	0.700	78	3.566	0.001

X9B.Time.to.Completion

	Value	Std.Error	DF	t-value	p-value
Intercept	12.560	1.422	78	8.832	0.000
Problem 2-1	5.713	1.290	78	4.427	0.000
Problem 3-2	0.443	1.262	78	0.351	0.727
Semester Spring 2011-Fall 2009	8.465	1.483	61	5.708	0.000
X6C.False.Alarm.Rate	35.614	12.920	78	2.756	0.007

APPENDIX T

PROCESS ANALYSIS RUBRIC FOR MEASURING STUDENT PROBLEM SOLVING ATTEMPTS

		Measure	Notes	Inadequate (Score of 0)	Adequate (Score of 0.5)	Exceptional (Score of 1)
Identify the problem	Completed	Explicit unknown value	□ Identified unknown	Did not identify final conditions	Identified final conditions but was incomplete or vague	Fully identified final conditions
	Accuracy	Correct Unknown value	□ Incorrect unknown	Did not solve for correct final condition		Correctly solved for final conditions
	Efficiency	Number of corrections to get correct unknown	□ NA if Above = 0	>2	1-2	0
Define the problem	Completed	Explicit definition	□ Restated problem □ Identify assumption □ Identified constraints	Did not explicitly define the problem	Completed 1-2 problem definition tasks	Completed all 3 problem definition tasks
	Accuracy	Correct definition	□ Incorrect assumption □ Ignored problem constraints	Did not correctly define the problem		Correctly defined the problem
	Efficiency	Number of corrections to get correct definition	□ NA if Above = 0	>2	1-2	0
Represent the problem	Completed	Explicit visual	□ Draw a Diagram □ Relate variables	No diagram drawn, no relationships indicated	Drew a diagram OR related variables	Diagram drawn with variable relationships indicated
	Accuracy	Correct representation	□ Incorrect representation □ Incorrectly relate variables	Did not correctly represent the problem (at least one error)		Correctly represented the problem (no errors)
	Efficiency	Number of corrections to get correct representation	□ NA if Above = 0	>2	1-2	0
Develop a solution strategy	Efficiency	Approach Strategy Used	□ Unable to determine strategy	Plug and chug Or Guess and Check	Segmentation OR Means-End Analysis	Chunking Or Forward Chaining

Organize knowledge	Completed	Explicit knowns and Equations	□ Identify known values □ Identify equation	Did not explicitly complete organization tasks	Utilized 1 information organization tasks	Utilized both information organization tasks
	Accuracy	Correct knowledge organization	□ Incorrect known values □ Misuse governing equation	Used wrong equation or misplaced several values	Used correct equation but misplaced some values	Equation set up correctly with correct values in correct places
	Efficiency	Number of corrections to get correct known values / equations	□ NA if Above = 0	>2	1-2	0
Allocate resources (Execution)	Completed	Execute tasks to arrive at solutions	□ Manipulate equation □ Derive units □ Use conversion factor □ Plug values in equation □ Document math □ Solve intermediate values	Work did not show evidence of execution tasks	Work showed evidence of 1-2 task types	Work showed evidence of at least 3 tasks
	Accuracy	Correct Execution of tasks (Mechanical)	□ Incorrectly manipulate equation □ Incorrect calculation □ Incorrect unit derivation	Did not correctly execute algebraic tasks		Correctly executed algebraic tasks
	Efficiency	Number of corrections to get correct mechanical execution	□ NA if Above = 0	>2	1-2	0
	Accuracy	Correct Execution of tasks (Management)	□ Inconsistent transcription □ Inconsistent units □ Incorrect unit assignment □ Missing units throughout	Did not correctly manage the execution of algebraic tasks		Correctly managed the execution of algebraic tasks
	Efficiency	Number of corrections to get correct mechanical execution	□ NA if Above = 0	>2	1-2	0
	Accuracy	Overproduction	□ Irrelevant Information	Used irrelevant information		Did not use irrelevant information
	Efficiency	Overprocessing		Erased correct work often (>2 times)	Erased correct work some (1-2 times)	Did not erase correct work
	Efficiency	Number of tasks		Upper 10%	10%-90%	Lower 10%

Monitoring Progress	Completed	Hit rate		≤0.25	0.25 < x < 0.5	>.5
	Accuracy	False alarm rate		≥0.5	0.2 < x < 0.5	0< x < 0.2
	Efficiency	Sensitivity (A')		[0.0-0.6)	[0.6-0.8)	[0.8-1.0]
Evaluate the solution	Completed	Check accuracy	□ Checked accuracy □ Indicated final answer	Did not check accuracy or indicate final answer	Checked accuracy or indicated final answer	Checked accuracy and indicated final answer
	Accuracy	Correct evaluation	□ Incorrectly manipulate equation □ Incorrect calculation □ Incorrect unit derivation	Checked accuracy but was flawed	Checked accuracy but was incomplete	Properly checked accuracy

Process Analysis Rubric for Measuring Student Problem Solving Attempts

	Performance Measures	Notes	Inadequate (Score of 0)	Adequate (Score of 0.5)	Exceptional (Score of 1)
Solution Accuracy	Answer Accuracy		Incorrect Answer or Gave Up	Correct Answer but Missing / Incorrect Units	Correct Answer
	Conceptual Errors	□ Incorrect assumptions □ Incorrect representation □ Incorrectly relate variables □ Misuse governing equation	Left more than 1 error remaining in the solution	Left 1 error remaining in the solution	Left 0 errors remaining in the solution
	Mechanical Errors	□ Incorrectly manipulate equation □ Incorrect calculation □ Incorrect unit derivation	Left more than 1 error remaining in the solution	Left 1 error remaining in the solution	Left 0 errors remaining in the solution
	Management Errors	□ Incorrect unknown value □ Ignored problem constraints □ Incorrect known value □ Inconsistent transcription □ Inconsistent units □ Incorrect unit assignment □ Missing Units Throughout □ Irrelevant information	Left more than 2 errors remaining in the solution	Left 1-2 errors remaining in the solution	Left 0 errors remaining in the solution
Process Efficiency	Error rate		More than 25%	5%<x<25%	0% ≤ x ≤ 5%
	Time to completion		Slowest 25%	Middle 50%	Fastest 25%

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