UNDERSTANDING THE MODELING SKILL SHIFT IN ENGINEERING: THE IMPACT OF SELF-EFFICACY, EPISTEMOLOGY, AND METACOGNITION

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ABSTRACT

A focus of engineering education is to prepare future engineers with problem solving, design and modeling skills. In engineering education, the former two skill areas have received copious attention making their way into the ABET criteria. Modeling, a representation containing the essential structure of an event in the real world, is a fundamental function of engineering, and an important academic skill that students develop during their undergraduate education. Yet the modeling process remains under-investigated, particularly in engineering, even though there is an increasing emphasis on modeling in engineering schools (Frey 2003). Research on modeling requires a deep understanding of multiple perspectives, that of cognition, affect, and knowledge expansion.

In this dissertation, the relationship between engineering modeling skills and students' cognitive backgrounds including self-efficacy, epistemic beliefs and metacognition is investigated using model-eliciting activities (MEAs). Data were collected from sophomore students at two time periods, as well as senior engineering students. The impact of each cognitive construct on change in modeling skills was measured using a growth curve model at the sophomore level, and ordinary least squares regression at the senior level.

Findings of this dissertation suggest that self-efficacy, through its direct and indirect (moderation or interaction term with time) impact, influences the growth of modeling abilities of an engineering student. When sophomore and senior modeling abilities are compared, the difference can be explained by varying self-efficacy levels. Epistemology influences modeling skill development such that the more sophisticated the student beliefs are, the higher the level of modeling ability students can attain, after controlling for the effects of conceptual learning, gender and GPA. This suggests that development of modeling ability may be constrained by the naiveté of one's personal epistemology. Finally, metacognition, or 'thinking about thinking', has an impact on the development of modeling strategies of students, when the impacts of four metacognitive dimensions are considered: awareness, planning, cognitive strategy and self-checking. Students who are better at self-checking show higher growth in their modeling abilities over the course of a year, compared to students who are less proficient at self-checking. The growth in modeling abilities is also moderated by the cognitive strategy and planning skills of the student. After some experience with modeling is attained, students who have enhanced skills in these two metacognitive dimensions are observed to do better in modeling. Therefore, inherent metacognitive abilities of students can positively affect the growth of modeling ability.

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1.0 INTRODUCTION

Modeling is a fundamental function of engineering and learning to model an engineering system is an important academic skill students develop during their undergraduate education. Yet, developing one's modeling ability is not trivial. There is increasing interest in modeling, particularly in mathematics and physics, as there are several investigations into what promotes one's modeling ability. Unfortunately in engineering, where modeling encompasses much more than mathematical formulations; there is a paucity of research in modeling relative to how students acquire their modeling skills. Thus, it is not surprising that there is an increasing emphasis on engineering modeling (Frey 2003). Further, at a time when research on thinking and learning brings together multiple perspectives; social cognition and beliefs of students are expected to play a role in development of modeling skills, research on bridging these two areas appears to be opportune.

This dissertation serves to extend this multi-perspective on modeling and investigates the impact of three cognitive constructs on growth of modeling ability: self-efficacy, epistemology and metacognition. Hence, we have the following objectives: (1) to describe the importance of modeling, the stages of modeling process, and what it means to develop modeling ability; (2) using these activities, to assess the impact of students' self-efficacy, epistemic beliefs and metacognitive abilities on development of students' modeling skills; and (3) to create and adapt the instruments necessary to engineering to correctly measure modeling ability as well as self-efficacy, epistemic beliefs and metacognitive abilities. To assess their modeling skills, we provide students with special modeling scenarios called model-eliciting activities (MEAs). As a side objective, therefore, we provide MEAs as a means for improving students' self-efficacy, epistemic beliefs and metacognitive abilities.

To achieve these objectives, we developed theoretical frameworks of hypotheses on how the self-efficacy, epistemic beliefs and metacognition influence modeling growth. We measured students' modeling ability longitudinally using data from sophomore (Fall 2009 and Spring 2010 terms), and a cohort of senior students. We conducted an experiment in which participants (engineering students) worked on two MEAs. In addition, students' cognitive backgrounds were assessed using instruments described in the methodology section.

The first of the measured social cognitive constructs, self-efficacy, refers to one's beliefs of how well she can perform a task of interest (Bandura 1986). An individual has high self-efficacy for a task when she believes that she possesses the capabilities necessary to successfully perform it. The body of rich empirical research on self-efficacy beliefs and educational outcomes dates back to the 1970s. Social cognitive theory has established that the individual differences or beliefs influence and predict performance. Students with higher levels of self-efficacy typically achieve higher outcomes in the assessed domain (Bandura 1997, Pajares 1996), have higher academic achievement (Multon, Brown, and Lent 1991), and display greater job performance (Stajkovic and Luthans 1998). Given prior literature, it is fitting to assert that self-efficacy should influence development of certain fundamental, critical engineering abilities, specifically modeling (Schreuders 2007).

Previous measurements of self-efficacy have employed proxies in the form of test scores, and assignment grades to generalize self-efficacy scales as overall self-efficacy. Conclusions from these measurements are that self-efficacy instruments that are not based on the concerned task provide results in contrast to the true nature of self-efficacy beliefs and carry less predictive value (Bandura 1997). In this dissertation, therefore, a scale entitled the "Engineering Modeling Self-efficacy Scale" (EMSS) was created to prevent measurement errors. It was tested to measure whether there are differences in self-efficacy levels of students from different disciplines and years.

The second construct, epistemology, is concerned with the nature of knowledge, justification, evidence, and related notions. Epistemic beliefs were shown to correlate with learning on multiple dimensions (Duell and Schommer-Aikins 2001, Bendixen and Hartley 2003), including metacognition (Hofer 2004, Bendixen and Hartley 2003), self-regulation (Muis 2007), comprehension (Hartley and Bendixen 2001), scientific argumentation and reasoning (Duschl and Osborne 2002, Sandoval 2003, Sandoval and Reiser 2004) and ability to solve a problem (Schommer-Aikins, Duell, and Hutter 2005). Sophistication levels of epistemic beliefs were used to test their impact on development of modeling skills.

The last construct, metacognition, is defined to be "the ability to reflect upon, understand, and control one's learning" (Schraw and Dennison, 1994, p. 460); and is a critical cognitive process that can impact a student's ability to learn to model. Operating through two separate mechanisms, knowledge about cognition and the knowledge about the regulation of cognition, metacognition includes both an awareness of cognition and an understanding of strategies to change cognitions by facilitating self-reflection, that of understanding and control of one's own cognitions. Therefore, there is reason to expect that the modeling strategies of students are influenced by their metacognitive properties. For each construct - self-efficacy, epistemology and metacognition, we developed a theoretical framework on how and why the background of self-efficacy, epistemology and metacognition can translate into growth in modeling ability. We discuss, in specific, the relationship between the use of MEAs and the three constructs. Collecting data from both sophomore and senior level engineering students over a year long period, we test whether metacognition impacts the growth of modeling abilities in engineering students.

The overarching results of this dissertation suggest that self-efficacy beliefs are similar within disciplines; and, as expected, often are higher for seniors compared to sophomore students, as well as for male engineering students compared to female. Tests showed that self-efficacy, epistemology and metacognition impact the development of modeling skills.

The rest of the dissertation is organized as follows. In the next section, we are providing a summary of the background on modeling and its characteristics, as well as modeling skill shift. Next, we describe the common methodology to all four studies in the dissertation including data collection and the instruments used to measure modeling outcomes, self-efficacy, epistemic beliefs and metacognition and interviews following the data collection. Following the methodology section, in the first study, we describe the creation of EMSS and build a theory of how self-efficacy is expected to influence the growth of modeling ability. Second study focuses on developing a framework to estimate the impact of epistemology and explains the tests conducted for assessing the significance of this impact. Third study follows the same methodology by creating the hypotheses and measuring the influence of metacognitive dimensions on modeling. Finally, in the fourth study, a report of strategies used in modeling is provided, using a qualitative and descriptive methodology. Following all four studies, we provide a specific overall summary section. This part of the dissertation aims to provide a quick review as well as suggestions for future research and implications, and includes a theory of propositions on growth of modeling, summary of the findings in all four studies, discussion of limitations and future work, and also a section of suggestions for the practitioners. Finally, a section is devoted to list the contributions of this dissertation to the literature of engineering.

2.0 LITERATURE SUMMARY ON MODELING

2.1 DEFINITION OF MODELING

In a broad definition, the term *model* refers to a simplified or idealized description or conception of a particular system, situation, or process, often in mathematical terms, that is put forward as a basis for theoretical or empirical understanding, or for calculations, predictions, etc.; as well as a conceptual or mental representation of something. The term *modeling* also refers to devise a model or simplified description of a phenomenon or system (Bodner, Gardner and Briggs 2005). Modeling is the essence of thinking and working scientifically (Harrison and Treagust 2000). Other definitions of modeling abound. Definitions of modeling from various authors are given in Figure 1.

Reference	Definition of Modeling
Lesh and Harel (2003)	Conceptual systems that generally tend to be expressed using a variety of interacting representational media – which may involve written symbols, spoken language, computer-based graphics, paper-based diagrams or graphs, or experience-based metaphors.
Voskoglou (1995)	An idealized (simplified) representation of a real-world system.
Gilbert (1997)	Representation of an idea, object, event, process, or system, which concentrates attention on certain aspects of the system.
Ingham and Gilbert (1991)	Facilitating scientific inquiry.
Johnson–Laird (1989)	Mental entities that people construct with which they reason; all of our knowledge of the world therefore depends on our ability to construct models of it.
Norman (1997)	To a target system or phenomenon with which we have a common experience or set of experiences.
Bower and Morrow (1990)	Representations of physical and social world which we manipulate when we think, plan, and try to explain events in that world.

Figure 1. Various definitions of modeling

According to the definitions in Figure 1, models are built to construct, describe or explain single or integrated systems. Narrowing these definitions for engineering; modeling can refer to: (i) a conceptual system for describing or explaining the relevant mathematical objects, relationships, actions, patterns, and regularities that are attributed to the problem solving situation, and (ii) accompanying procedures for generating useful constructions, manipulations, or predictions for achieving clearly recognized goals (Lesh and Harel 2003). A model is comprised of fragments; in other words, abstractions of some physical system, mechanism, structure that lead to inclusion of constraints to the overall model behavior. The selection of model fragments and the way to compose small fragments into bigger model fragments is what creates the aggregate model (Blum et al. 2007).

In this dissertation, the term *modeling* is used to describe the process of constructing a representation of a real-world system. The properties, classifications and descriptions of modeling process are provided next.

2.2 CATEGORIES OF MODELS

One can see that models are mentioned in three different ways in the literature: as content (study of modeling itself), as a vehicle (use of modeling as a tool to understand other phenomena) and as a way to reflect on the society (particularly for mathematics society, understanding the role of modeling for students and instructors) (Barbosa 2006). Accordingly, models have been categorized in various ways by different studies.

Stockburger (1996) classified models into two groups: (1) physical, as in a product prototype or architectural model of a building or (2) symbolic models, such as conceptual or mathematical models, which are constructed using a natural (e.g., English, German) or a formal language (e.g., algebra, computer language). According to the author, models can further be divided into several other categories like analytical models, statistical models, structural models, numerical models, etc. The categorization of physical vs. symbolic models resembles the categorization of analogical models (scaled or exaggerated objects, symbols, equations, graphs, diagrams, and maps) vs. simulation models.

Another classification is mental models that exist within the mind of individual and physical and conceptual models that are shared among members of a community (Greca and Moreira 2000). Mental models are defined as internal, personal, idiosyncratic, incomplete, unstable and essentially functional; whereas conceptual models are external representations that are shared by a given community.

A classification of models based on the thinking process is suggested by Gilbert (1997) as (1) a mental model is product of an individual's thought process; (2) an expressed model is produced when a mental model is placed in the public domain through action, speech, or writing; (3) a consensus model is an expressed model that has been generally accepted among a community of scientists; and (4) a teaching model is an expressed model that was specifically developed to help students understand an historical or conceptual model.

The most common models in engineering can be grouped into conceptual and calculational models (Tsang 1991). According to this classification, a conceptual model consists of three main components: structure (physical structure of the system), processes (physical, chemical, etc. phenomena that take place in the system), and boundary and initial conditions (constant or time dependent conditions imposed on the boundaries of the model domain).

Calculational models are the computational (mathematical model, computer code, etc.) representations of the system that solves a given set of equations with given inputs by numerical manipulations. In such, a calculational model can involve a set of mathematical equations, a computer code, or any system that estimates the performance criteria of the model. The relationship between a conceptual and a calculational model are given in Figure 2, as originally represented by Tsang (1991). In this figure, the author refers to the mathematical or calculational model with the word ‘code’.

Structure and boundary and initial conditions are dependent on the system and scale of the system and both appear within data and the calculational model. These involve constraints on the representation of the real-world system as well as the analysis of extreme cases which can exist in the system. Processes can be described by mathematical equations, as well as conceptual or pictorial relationships; and they also can be solved by the calculational model.

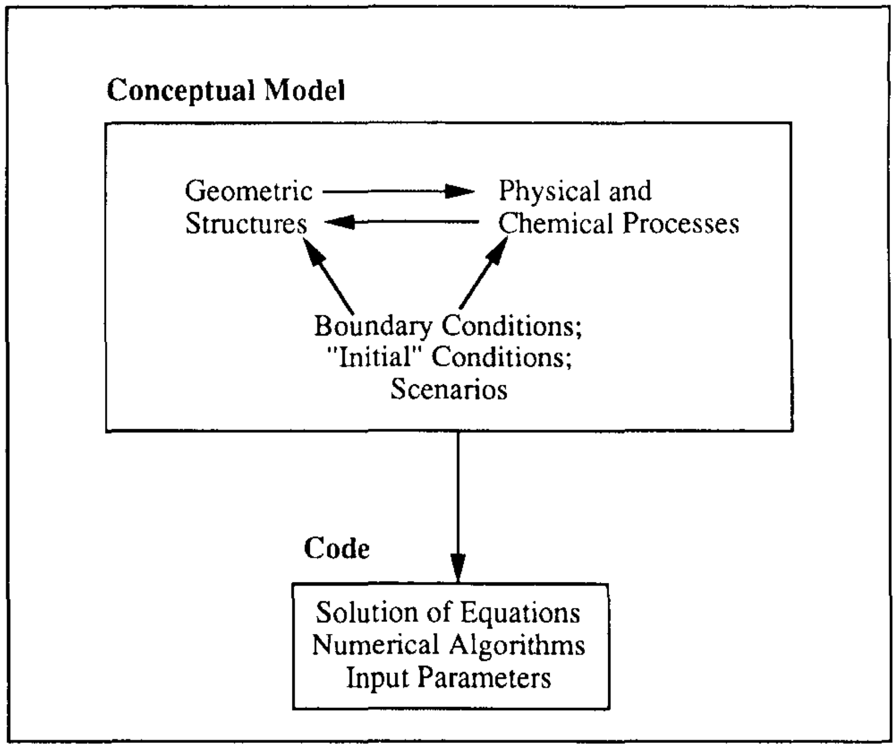

Figure 2. Relation of conceptual and calculational model (Tsang 1991)

2.3 PROPERTIES OF MODELS

Various properties of modeling are mentioned in different research studies. A summary of the major properties of models is presented in the following list:

2.3.1 Representation

In models, variables and the relations between the variables by operators are represented by symbols, or figures, logic, language, etc. (Murthy 1979). The systems integrated in real life are decomposed and translated into languages of modeling and represented.

2.3.2 Association with Real World

The structure of how models relate to real life should take place as follows: variables should be capable of being associated with physical quantities in an external (real or physical) world; operators in the model should be capable of being associated with relationships between the physical variables of the external world Murthy (1979).

2.3.3 Simplification/ Scaling Down of External World

In general, models should not be related to the external world on a one to-one basis. This implies that the model does not contain information regarding all aspects of the external world. The amount of information on the external world contained in a mathematical model depends on how it is to be used; i.e., on the goals of the model builder (Murthy 1979). This implies that the same system of the external world can have different mathematical models depending on the final purpose; where no single model is better than the others. This property can also relate to what Smith (1996) calls *cost-effectiveness*: It is more cost-effective to use the model for this purpose than to use the referent itself. Rothenberg (1989) compliments this view by suggesting that modeling is “the cost-effective use of something in place of something else for some cognitive purpose.”

2.3.4 Purpose

Smith (1996) says that a model represents ‘reality for the given purpose’, and it is an ‘abstraction of reality in the sense that it cannot represent all aspects of reality’. It has an intended cognitive purpose with respect to its referent.

2.3.5 Incompleteness

Because a model is a scaled down representation, no model includes every aspect of the real world. In order to create a model, an engineer must make some assumptions about the essential structure and relationships of objects and/or events in the real world. These assumptions are about what is necessary or important to explain the phenomena (Stockburger 1996).

2.3.6 Ease of manipulation

Models are easy to manipulate and experiment on, compared to the real world. An engineer can manipulate the model by changing the assumptions, variables, data or relationships, and observe a prediction of what might happen in reality, rather than doing a similar operation in the real world. Manipulating the model rather than the real life system is more convenient, simpler, less time and money consuming, and results that might be catastrophic in real life can be prevented (Stockburger 1996). It is noted that changing symbolic models is generally much easier than changing physical models.

2.3.7 Use of Heuristics and Strategies

An important property of modeling in engineering is the use of heuristics (Koen 1985). According to this view, modeling goes hand in hand with heuristic building: although they do not always guarantee a solution or they may contradict or give different answers to the same question; heuristics help solving difficult problems or reduce the solution time therefore the cost significantly. Further, heuristics are solved based on the context (considering the assumptions made) instead of the holistic system.

Further, typical engineering heuristics that are employed in modeling are classified as: ‘(1) rules of thumb and orders of magnitude; (2) factors of safety; (3) heuristics that determine the engineer's attitude toward his or her work; (4) heuristics that engineers use to keep risk within acceptable bounds; and (5) rules of thumb that are important in resource allocation’ (Koen 1985).

2.4 MODELING PROCESS

The modeling process is defined as ‘to specify a description of a device and its operating environment that can be used to infer some information about the device (Gruber 1992)’. The process (of mathematical modeling) is sometimes given the name *modeling cycle* (Kaiser 2005). Modeling cycles are often characterized by diagrammatic representations (Galbraith and Stillman 2006). In mathematics education, for example, researchers often use diagrams to analyze students’ modeling. Other methods of analysis of modeling processes are often carried through use of discourse or use of following categories of verbal information: mathematical (ideas belonging to mathematics); technological (ideas referring to techniques of building the mathematical model) and reflexive (criteria used in building a model and its consequences) (Barbosa 2006).

Modeling process involves making decisions about relevant physical domains, abstractions, approximations, and other assumptions (Gruber 1992). Depending on the purpose and focus of the research modeling processes might look different (Crouch and Haines 2004). Some of these different descriptions of the modeling processes are given next. Thus modeling is a search of a space defined by multiple criteria. Modeling process is constructive since it involves putting together partial solutions under constraints and explicitly representing the information used to select, assemble, and evaluate the model.

Lesh and Harel (2003) focus on the transitions from one stage within the modeling process and define the stages as quantifying, organizing, systematizing, dimensionalizing, coordinatizing, and (in general) mathematizing objects, relations, operations, patterns, or rules that are attributed to the modeled system.

A formulation of the process of forming a model in four stages is given in Figure 3 from Stockburger (1996).

Stage	**Description**
Simplification/ Idealization	Identifying the relevant features of the real world.
Representation/ Measurement	Translating 'word problems' to formal languages. This process is called representation of the world. In statistics, the symbols of algebra (numbers) are given meaning in a process called *measurement*.
Manipulation/ Transformation	Sentences in the language are transformed into other statements in the language. In this manner implications of the model are derived.
Verification	Selected implications derived in the previous stage are compared with experiments or observations in the real world.

Figure 3. Process of forming a model (Stockburger 1996)

These four stages and their relationship to one another are illustrated in Figure 4 below (Stockburger 1996).

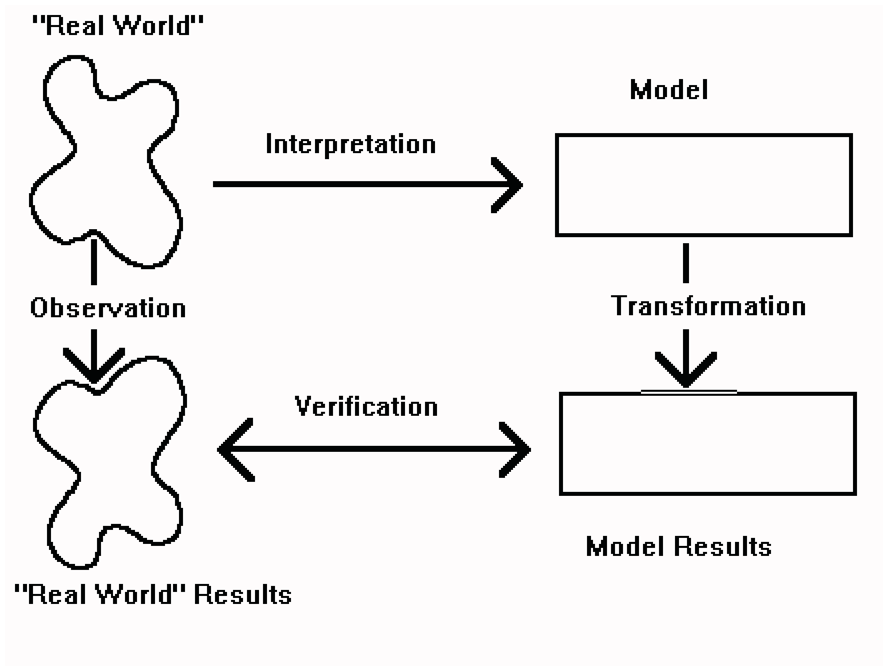

Figure 4. Stockburger's (1996) modeling process and the relationships to real world

Stockburger's model is an intuitive and fundamental description of what is happening in modeling. More detailed process descriptions follow such basic models. For example, Van Der Schaff et al. (2006) define the process of modeling as a subset of problem solving and define four steps, but add each some several sub-steps of the modeling process, as given in Figure 5.

Stage	Description of Stage and Sub-steps
General Analysis	• Obtain a clear view on the question that is to be answered using the model, in what way the model is going to help to solve the problem and what system the problem is related to. • Determine the function of the model, what question should be answered by the model. • Describe the system to be modeled in words. • Make a schematic drawing of the system to be modeled.
Detailed Analysis	• Make assumptions explicit. • Define the system boundaries & define subsystems. • Make a drawing including all available data. • Determine which variables and parameters could be important.
Compose the Model	• Search for and select a set of usable standard equations. • Check the number of equations and the number of unknowns. • Check the units.
Answer the Question / Evaluate	• Use the model to answer the question. • Evaluate the answer.

Figure 5. Process of forming a model Van der Schaff et al. (2006)

Mathematical modeling process is demonstrated as illustrated in Figure 6, which is a reference to Arleback (2009), Blum and Leiss (2007) and Borromeo Ferri (2006, p. 92). Accordingly, Borromeo Ferri (2006) describes the phases of mathematical modeling as (1) understanding the task, (2) simplifying/structuring the task, (3) mathematizing, (4) working mathematically, (5) interpreting, and (6) validating. During these steps, the model builder makes decisions about choice of the domain of relevant physical phenomena to model, which aspects of the system to use, determines appropriate assumptions to make and chooses abstractions at the appropriate level of detail.

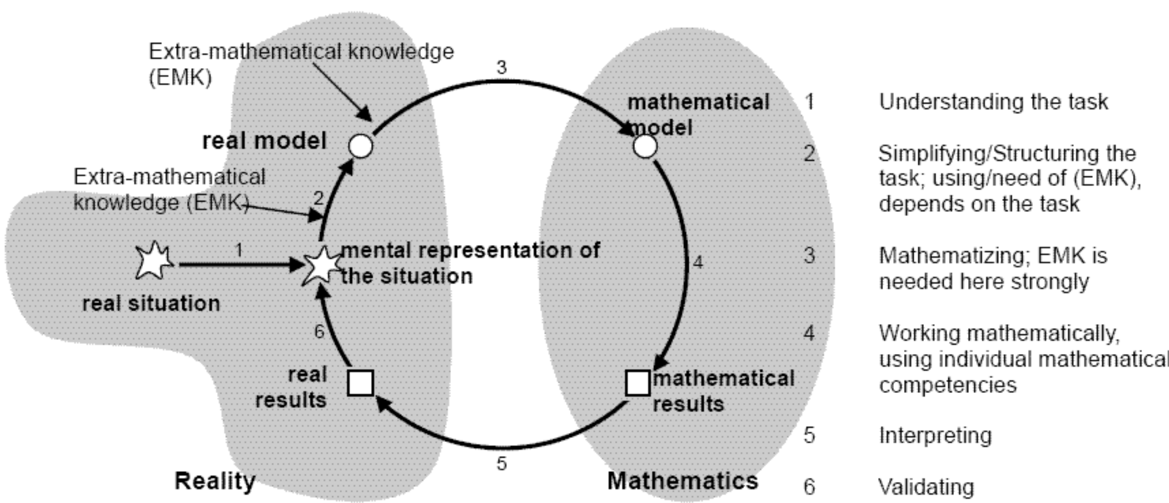

Figure 6. The mathematical modeling cycle (Blum and Leiss 2007)

Among the studies that cover modeling process, the one of Tsang (1991) is well suited to modeling process of engineering. His steps of a modeling process are given in Figure 7.

Modeling Stage (Notation)	Description
Review and Evaluation of Data (RED)	Searching a database to obtain numbers necessary to calculate results of a model; trying to obtain as good as data as possible to represent the overall picture of the site and relevant processes occurring.
Conceptual Modeling & Potential Scenarios (CON)	Abstracting the essence of the database to construct the structure of the physical model, to identify the physical and chemical processes involved in the system, and to determine the appropriate boundary and initial conditions.
Establishment of Performance Criteria (EPS)	Modifying the performance criteria for something plausible yet still acceptable for the problem on hand; where a performance criterion is defined as the quantity of interest that the model is asked to predict.
Development of Calculational Models/ Associated Parameters (CAL)	Creating simplified models using the conceptual models (author refers them as calculational models) and defining lumped parameters (parameter values averaged over spatial regions, and elementary parameters).
Modeling Calculations, Sensitivity Analysis (CUS)	Calculations (author considers computer runs), creating tables of results and graphical outputs. Studying the sensitivity of the results on parameter or data uncertainties.
Results Evaluation (RE)	Understanding and evaluating the calculational results. The results, including the estimated uncertainties are evaluated according to the performance criteria; where uncertainties may arise from data and the steps preceding, such as choice of a calculational model.
Validation / Verification (VV)	Ensuring that the model is built right and the right model is built.

Figure 7. Tsang’s (1991) modeling stages

It is clear from this model that the processes of modeling in engineering and mathematics are very similar, and the modeling process description of engineering comprehends the process of mathematical modeling. Tsang's model, in particular, includes all the steps in Blum's model.

Tsang, Van der Schaff et al., Blum et al. and Stockburger models show that modeling processes can be defined in different ways, but the descriptions are similar. Among these, Tsang's modeling process descriptions seem to be the most detailed and suited. Thus, in this dissertation, this process model is embraced.

2.5 MODELING ABILITY GROWTH

The dictionary definition of expertise is mechanism(s) underlying the superior achievement of an expert, and an expert is one who has acquired special skill in or knowledge of a particular subject through professional training and practical experience (Webster's dictionary, 1976, p. 800). Accordingly, skill shift, or growth in ability is this process of becoming an expert, or gaining expertise.

A growth in modeling ability is the shift occurring in observable and non-observable properties of modeling processes of students. According to this definition, skill shift is a path of describable change in modeling strategies (Chase and Simon 1973). It is difficult to determine in advance whether this path is similar for different individuals or whether it is based on personal characteristics. Thus, this dissertation in-part investigates if there are identifiable patterns of change in how students go about modeling an engineering system as their domain knowledge, modeling experience, and cognitive processes enhance or change. In the following figure, the growth of modeling ability in engineering students is represented. The figure shows that there should be a change in the strategies of modeling as engineering students are learning new domain specific information; gain expertise and their backgrounds allow them to learn.

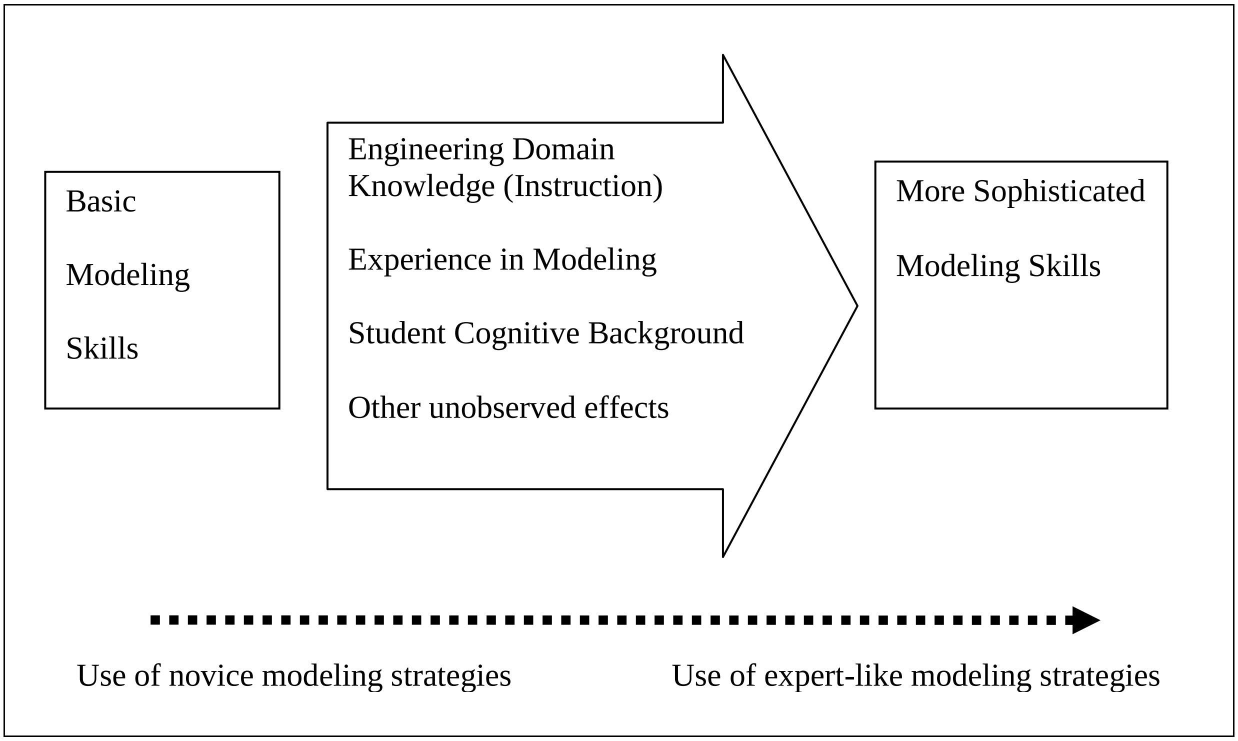

Figure 8. Modeling skill shift

In various disciplines, like physics and mathematics, the differences between expert and novice strategies have been noted for problem solving (Chase and Simon 1973, Chi, Feltovich, and Glaser 1981). Most of this analysis has been conducted using well-structured problems and puzzles such as chess (Chase and Simon 1973) and physics problems (Champagne, Gunston and Klopfer 1983, Chi, Feltovich and Glaser 1981). Among such differences is an expert having a substantial body of organized knowledge (Chase and Simon 1973). In physics problem solving, Chi, Feltovich and Glaser (1981) notes the differences in time to solve a problem and pause times. Simon and Simon (1978) notes that there is a significant difference in the time it takes a novice to solve the problem, such as a four to one ratio. This posits that in terms of time, experts are more efficient in reaching a solution. These time differences are measured in the context of well-defined problems and may not replicate in presence of open ended problems. Chi et al. mentions the difference in the pause times taken between novices and experts. Experts tend to group their information in chunks. Thus while solving a problem they tend to remember a sequence of equations with small inter-response times followed by a long pause. While experts are more likely to focus on hidden relational properties of a problem, novices are more likely to focus on less important surface features of a problem. When presented with deduction problems, novices often tended to ignore the argument's logic (i.e., its deep structure) while relying on the argument's surface features, such as content and believability (Evans, Newstead, Byrne, 1993; Johnson- Laird and Byrne, 1991).

It is suggested that the contrast of novice and expert differences may be subject to environmental constraints such as context and the availability of time and other resources. This can explain the differences that exist among students and professionals in modeling (Barbosa 2006). For example, while trying to do their best in an exercise, students often use a judgment on how they are expected to approach a problem. Professionals, on the other hand, are expected to find the best solution possible, and cannot use expectations of management as a clue. To decrease such environmental effects of modeling practices of students and professionals, more implementations of ill-defined, project based, open ended problems are integrated into engineering curriculums.

In engineering, students deal with ‘ill-defined’ problems, where the actual problem, constraints, data, etc. are not clearly defined; and the solution to the problem is open ended and the complexity of real life is reflected. Therefore, each engineering problem presents a real life model. From an engineering management point of view, the goal of the engineer is to create simple models with high representative power. In general, the greater the number of simplifying assumptions made about the essential structure of the real world, the simpler the model. A trade-off occurs between the power of the model and the number of simplifying assumptions made about the world. The engineer must decide at what point the gain in the explanatory power of the model no longer warrants the additional complexity of the model. A characteristic of a good model is a series of iterative 'modeling cycles' where trial descriptions (constructions, explanations) are tested and revised repeatedly (Lesh and Harel 2003). Thus, as engineering students become more aware of the engineering contexts, domain knowledge and gain expertise, differences in modeling strategies can become clear.

Tsang (1991) suggests that a difference between novices and experts is the inclusion or exclusion of validation. It is expected that senior students provide more justification, sensitivity analysis, or references to another model while creating their own, compared to the novice engineers. A list of different validity types used by engineering modelers is provided in Figure 9. Based on the expectancy of use by novice or experienced student, each type is noted, and the explanation for why they are likely to be used by these groups of engineering students are given next.

Validity Type	Description	Likely to be used by
Event Validity	Initial validation of qualitative nature, in which events of occurrences of a model is compared to those of real system.	Novice & expert students
Face Validity	Considered as part of peer review, asking people knowledgeable in the field whether the model is reasonable; checking for correctness of model's flowchart and input-output relations.	Novice and expert students
Tracing	Tracing the behavior of different elements or entities of a model to determine if the logic and the program are correct.	Expert students
Historical Methods	Examining the model's assumptions in theory, observations, general knowledge, and intuition; validating each of model's assumptions, where possible by empirically testing them; comparing the input-output relationship of the model to the field behavior.	Expert students
Internal Validity	Determining the stochastic variability in the model by using several realizations in the model.	Expert students
Historical Data Validation	If historical data exists for a given site, part of the data may be used to construct the model and the remaining to check against the calculated results.	Expert students
Predictive Validation	The model is used to provide predictions and further measurements are made to check these predictions.	Expert students
Turing Tests	Asking people knowledgeable in the field if they can discriminate between model output and field observations.	Expert students

Figure 9. Types of validity in engineering modeling

According to the figure, expert student modelers can be expected to use any of the validity types and can use some or all common forms of validity. Event and face validity are used more often, and more frequently in those of novice modelers. Students claim the model they build ‘looks all right’. They make overall statements on why it is appropriate to use a certain methodology.

In addition to the types added by Tsang (1991), construct validity (without calculations of construct validity measures) and external validity are rather common in upper level modeling skills. It may be possible that after experiencing multiple modeling cases and having the domain knowledge, an engineering student will have experienced a shift of modeling ability. The goal of this research is to understand the differences between weak and strong modeling strategies through an analysis of different student modeling exercises and hopefully translate these analyses into practices to elevate most of the students to the level of strong modelers.

The expectance characteristics of more experienced modelers are based on the model of De Corte (1993) which proposes an analysis of good learning characteristics. Using this study as an example, in this dissertation, it is expected that more experienced students should have the six qualitative characteristics in their modeling strategies. Accordingly, experienced strategies should be as follows:

1. ***Constructive Learning:*** To be constructive means that learning is a student centered process where the learner creates meanings through cognitive processing. When modeling abilities are developed, students should be expected to not just transfer knowledge and skills as passive recipients, but they should be processing the meaning of the exercise. This links strongly back into metacognitive skills of the student. If she is

able to reflect on the exercise, the student can not only implement already known models and methods, but can adjust, create and expand models using their own skills.

2. ***Cumulative Learning:*** Learning is based on formal as well as informal knowledge and cognitive structures and is seen as a linking process between prior and new knowledge, and skills. Accordingly, when students develop modeling ability, they should be expected use multidisciplinary knowledge while creating models, for example, knowledge from the areas of statistics, engineering economics, ethics, etc. This 'cumulative learning' property ties nicely back to the cognitive-strategy dimension of metacognition, where a student is expected to use multiple strategies to model a real-world system, if better at metacognition. Instruction is definitely key in this process in that the more approaches the students learn, the more flexible they are in implementing them.
3. ***Co-operative Learning:*** Learning has a strong social character (Slavin 1990). Social interaction can lead to a process of knowledge construction and transformation where learners create common concepts and skills cooperatively (Sharan and Sharan 1992). Accordingly, more experienced students are expected to make better use of the team processes and social interaction while creating a model. The co-operative learning property fits into the MEA implementation, where modeling is not only an individual process, but a team endeavor.

4. ***Self-regulated Learning:*** Self-regulated learning ties back to self-efficacy and meta-cognitive characteristics such as planning, managing and reflecting. Self-regulation means that a student has the skills to design, control and guide his or her learning process, is willing to learn and is able to evaluate and reflect on the entire learning process. As will be mentioned in the metacognition section subsequently, more experienced modelers are expected to have a higher level of awareness of their own cognitive processes.
5. ***Goal-oriented Learning:*** Effective, meaningful learning is facilitated by explicit awareness of an orientation towards a goal. If we see good learning as a constructive, cumulative, co-operative and self-regulated transformative action it is natural to suppose that good learning also requires student stated learning goals. In the case of modeling skills, experienced modelers, students should be able to set learning goals for the modeling exercises that they are working on.
6. ***Contextual Learning:*** Learning can be empowered by linking it to real life contexts where both social and physical components exist as such. The MEAs as a measurement tool of modeling also fits into this property, since the models are all given in a real-world context. When students develop better modeling abilities, one could expect that they relate their in-class modeling exercises to the real-world problems they face.

Based on these characteristics; experienced modelers can be expected to not just use domain knowledge, but also be able to generate further meanings, conceptions, and be able to put this knowledge in context and in practice, particularly in the context of solving MEA-like problems, which are framed in real-life stories. Students who develop better modeling abilities can be expected to use the information they have learned in the past with the new information they gain and use them in conjunction while creating a model. They should be able to regulate the modeling task on their own overall; reflect on their thinking process, and identify the objective of the modeling task clearly.

Finally, good modelers should be able to integrate their learning and practice to their social environment. Learning should not only be an individual achievement, but should extend to the team members and other class-mates. Students gain modeling abilities can be expected to communicate and apply what they learned in modeling, and use them for real life problems they encounter in the future.

3.0 METHODOLOGY

In this section, we describe the approach used to test the impact of the three cognitive constructs on students' ability to model. We first describe our data; and then describe the method of testing on development of modeling ability.

3.1 DATA COLLECTION

A data set from 91 students (seniors and sophomore industrial engineering students) was collected. The students in this group completed the instruments (to be described) to measure their level of self-efficacy, epistemic beliefs and metacognition, as well as their modeling skills.

The participants were given course credit and payment (as in the case of sophomores) or were paid for their time and effort (seniors). Thirty percent of the sample was female, which is proportional to the engineering student body at the University of Pittsburgh. Of the respondents, 82% were between the ages of 18 and 22 years; 10% were between the ages 23 to 27 years; and 3% were between 28 and 32. The students' ethnicity was not reported as part of this research work, but ethnicity was proportional to the engineering student body at the University of Pittsburgh. Further, all subjects were fluent in writing and speaking English. Instruments for the dissertation were administered via the web (with the exception of a sample of civil engineering students who were given a paper-pencil version of the self-efficacy instrument). Proper human subjects' clearance was obtained for this research and for this publication.

3.1.1 Procedure

The sample consisted of three cohorts of students (referred to as cohorts I, II and III). Cohort I involved first semester sophomore level industrial engineering students (n=49, 31% female). Data from these students were collected during the fall 2009. Cohort II students included second semester sophomore level industrial engineering (n=51, 32 % female), of which data were collected during spring 2010. Since University of Pittsburgh is a semester based institution; cohorts I and II capture the entire sophomore population for this particular engineering program. Thirty-nine students overlapped between cohort I and cohort II students. All students in cohort I and cohort II participated in the study in exchange for course credit and payment ($40). Cohort III included senior level industrial engineering students (n=41, 31% female). These students participated in the experiment in exchange for monetary payment ($80). Nine of the students left the experiment prior to completion, resulting in a final sample size of n=32.

To determine each student's modeling ability, two modeling exercises (i.e., Model Eliciting Activities or MEA from here on) were assigned per cohort. The two exercises given in this dissertation were the Tire Reliability and CNC Machine MEAs, (please visit www.modelsandmodeling.net for a copy of these exercises, or see Appendices), both of which are simulated open ended real life problems that involved or ideally required use of statistical concepts like mean, standard deviation, probability plots, goodness of fit tests, and knowledge of various distributions. Further, the MEAs are built around engineering systems that potentially require engineering economy knowledge domain as well; and it is possible for students to solve the models in another creative engineering approach of their own. Participating students were asked to solve the exercise in teams of three to four students. Students turned in their solution approach in the form of written memorandums.

Students of cohort I were given MEA 1 (Tire MEA) first and MEA 2 (CNC Machine MEA) next. In cohort II, the order was reversed. The reversed order was done to properly incorporate the MEAs into the course curriculum. Students did not receive feedback about the solution after the first time, and from a descriptive analysis of the solutions received, it is noted that students used different methodologies in modeling the exercises in both sessions.

Senior students of cohort III were given the exercises in the same order as cohort I. By providing the students the same exercises, we were able to (1) monitor the different modeling strategies students use at different times of their education, and (2) control for the differences in different modeling exercises. It is possible that the nature of the modeling exercise can cause differences in estimation of the effect of epistemic beliefs; therefore, to eliminate such differences, we opted to use the same exercises.

3.2 MEASURES

3.2.1 Modeling Skills Assessment

Assessment of modeling skills was carried out by analyzing student responses to the MEAs. A grading sheet was developed and used to assess and evaluate the resulting student models. This grading sheet was based on the MEA development principles and Tsang's (1991) modeling process definitions; hence, the grading sheet specifically addresses each of the seven modeling steps, as given in Figure 10. Prior to use in this experiment, a grading sheet was tested on pilot data.

Grade	DESCRIPTION	ELEMENT	
	Ability to identify the correct data to use, can make the appropriate research for acquisition of the data necessary	**Review and Evaluation of Data**	**Elements of Modeling**
	Ability to set relationships between the parameters of the model, simplify the real word using reasonable assumptions	**Development of Conceptual Model and Potential Scenarios**	
	Ability to set the goal and the ultimate values that the model is trying to achieve.	**Establishment of Performance Criteria**	
	Ability to choose or develop the right mathematical model or computational code for the problem	**Construction of Calculational Models and Determination of the \Associated Lumped Parameters**	
	Carrying out calculations correctly, conducting sensitivity analysis, identifying the uncertainty in results	**Model Calculations, Sensitivity Analysis and Uncertainty Analysis**	
	Interpreting numerical results correctly	**Results Evaluation**	
	Validating the numerical results, validation of the model	**Validation**	

Figure 10. Assessment sheet for the modeling outcomes

For each grading element, the student's memorandum is assessed and a rating between one and six is given. The summation of the individual elements provides the modeling level. The measurement was conducted by two separate researchers for reliability. A high reliability score was maintained for between the researchers to ensure measurement error was eliminated (i.e., score between the two researchers ranged between 0.75 and 0.94 for different cohorts). The average of the two ratings of the two researchers was used as the final modeling level score.

For cohorts I and II, the measurement of modeling skills followed a longitudinal assessment. This included implementation of two types of MEAs over four time points: September 2009 (Time point 1=T1), November 2009 (T2), January 2010 (T3) and April 2010 (T4). Implementation of the exercises were based on course syllabus, but followed a time gap of seven to nine weeks between MEA exercises. Cohort III was data was collected separately and not in a longitudinal manner. The longitudinal measurement means and standard deviations were as follows:

Table 1. Modeling outcome measurements – longitudinal

	Cohort I (n=49)				**Cohort II (n=51)**			
Modeling stage	**Tire MEA Grade (out of six)**		**CNC Machine MEA Grade (out of six)**		**CNC Machine MEA Grade (out of six)**		**Tire MEA Grade (out of six)**	
	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev
RED	2.15	0.90	3.59	1.08	3.85	0.83	4.06	0.67
CON	2.04	1.00	3.02	1.05	3.8	0.94	3.58	0.82
EPS	2.76	0.65	3.02	1.16	3.96	1.24	4.10	0.83
CAL	2.04	1.58	2.68	1.23	3.97	1.18	3.59	0.78
CAL	2.32	1.00	2.10	0.97	3.29	0.90	3.88	0.87
RE	2.04	0.41	2.12	1.26	2.92	1.05	3.71	0.88
VV	0.04	0.28	0.31	0.74	1.40	1.50	1.04	1.50

3.2.2 Self-Efficacy Beliefs Assessment

A specific self-efficacy scale titled Engineering Modeling Self-efficacy Scale (EMSS) was developed for this study on the domain of engineering modeling. The development and use of this scale are given in detail in Study 1, section 4.4. The scale can be seen in Appendix A.

A factor analysis of the instrument resulted in seven dimensions of engineering modeling self-efficacy, namely Review and Evaluation of Data Self-efficacy (SE_{RED}), Process Modeling Self-efficacy (SE_{PM}), Conceptual Modeling & Potential Scenarios Self-efficacy (SE_{CON}), Establishment of Performance Criteria Self-efficacy (SE_{EPS}), Interpretation and Evaluation Self-efficacy (SE_{IE}), Calculational Model Self-efficacy (SE_{CAL}) and Uncertainty and Validation Self-efficacy (SE_{UV}). All throughout the document, these dimensions are represented by the letters SE with the subscripts relating to the specific dimension name.

The mean and standard deviation of each dimension for the sophomore and seniors are given in Table 2. According to the table, there is an increasing trend in each dimension of self-efficacy from the sophomore to senior year. The analysis of this trend is conducted in detail in Study 1 as well.

Table 2. Mean and standard deviations of the self-efficacy level

Modeling Self-efficacy Factor (Notation)	**Cohort I mean (stdev) n=49**	**Cohort II mean (stdev) n=51**	**Cohort III mean(stdev) n=32**
Review and Evaluation of Data (SE_{RED})	3.75 (0.51)	3.74 (0.56)	3.84 (0.50)
Process Modeling (SE_{PM})	3.48 (0.54)	3.51 (0.61)	3.86 (0.50)
Conceptual Modeling (SE_{CON})	3.69 (0.51)	3.66 (0.64)	3.76 (0.59)
Establishment of Performance Criteria (SE_{EPS})	3.53 (0.61)	3.57 (0.65)	3.8 (0.70)
Interpretation and Evaluation (SE_{IE})	3.27 (0.69)	3.28 (0.74)	3.79 (0.49)
Calculational Model (SE_{CAL})	2.78 (0.71)	2.82 (0.74)	3.14 (0.82)
Uncertainty and Validation (SE_{UV})	3.38 (0.63)	3.37 (0.72)	3.77 (0.52)

3.2.3 Epistemic Beliefs

Different conceptualizations of epistemic beliefs tend to suggest different research methods. For example, studies focusing on epistemic cognition and cognitive resources tend to use qualitative methodologies, while studies of epistemic beliefs largely use quantitative data. Since the nature of the current dissertation is geared towards testing claims, we followed a quantitative approach.

According to Maggioni and Parkinson (2008), epistemic beliefs are composed of stable and semi-independent dimensions. This finding suggests that while learning occurs, epistemic beliefs of individuals remain relatively stable. Based on this suggestion, in our study, measurement of epistemic beliefs has not been repeated over different time points, whereas outcomes of learning have been repeatedly measured.

Epistemic beliefs were assessed using the Epistemic Beliefs Inventory (EBI) (Schraw, Dunkle and Bendixen 2002). The item is given in Appendix B and it consists of 32 elements that tend to cover the five dimensions previously mentioned using a scale ranging from one to five (1= do not agree at all, 5= completely agree).

Based on the median level, we then coded each student as being high or low on each of the five dimensions and created binary dummy variables to represent them. Therefore, students were equally divided on each epistemic dimension and as having either low or high strength in their beliefs. These binary variables were subsequently used in growth curve models and regressions.

3.2.3.1 Confirmatory Factor Analysis on EBI

EBI has been subject to many different interpretations. Therefore, it is found useful to conduct a confirmatory factor analyses (CFA) with principal components method, utilizing SAS 9.2 on the EBI responses. Before the analysis of the factor structure, each item's reliability (i.e., Cronbach's alpha) and discrimination power were analyzed. We checked for items with negative item-total correlation or items with item-total correlation lower than 0.10; and dropped these items from the analysis. This resulted in eight items being eliminated from the 32 item instrument.

Schommer's description (1990) of personal epistemology involved independent beliefs conceptualized about the simplicity, certainty, and source of knowledge, as well as beliefs about the control and speed of knowledge acquisition. The hypothesized five dimensions of epistemology were as follows:

1. *Simple Knowledge:* ranges from the belief that knowledge is best characterized as isolated bits and pieces to the belief that knowledge is best characterized as highly interrelated concepts;

2. *Certain Knowledge*: ranges from the belief that knowledge is absolute and unchanging to the belief that knowledge is tentative and evolving;

3. *Innate Ability (Fixed Ability)*: ranges from the belief that ability to learn is given at birth to the view that ability to learn can be increased;

4. *Quick Learning*: ranges from the belief that learning takes place quickly or not at all to the belief that learning is gradual;

5. *Source of Knowledge* (*Omniscient Authority*): ranges from the belief that knowledge is handed down by authority to the belief that knowledge is derived from reason.

Similar to Schraw, Dunkle and Bendixen (2002), our reliability analysis resulted in Cronbach's alpha ranging between 0.4 and 0.7. Although 0.4 appears to be low, it is in accordance with the reliability levels cited in prior studies using this instrument; thus, we chose to keep all factors in this study. Table 3 demonstrates the means and standard deviations for each epistemic dimension. The score of each dimension was obtained by summing the item scores and then dividing it by the number of items in the dimension. Some of the items were reverse scored; and thus an epistemic dimension can take a negative or positive value. The table provides for each of the dimension the possible range of values, as well as a theoretical mean value based on this range.

Table 3. Means and standard deviations of epistemic beliefs

Epistemic Dimensions	**Cohort I Sophomore (mean/ std) n=49**	**Cohort II Sophomore (mean/ std) n=51**	**Cohort III Senior (mean/ std) n=32**
Simple Knowledge (Range: -0.4 to 2.6, theoretical mean: 1.1)	0.64 (0.35)	0.64 (0.35)	0.50 (0.39)
Innate Ability (Range: 1 to 5, theoretical mean: 3)	2.87 (0.65)	2.86 (0.71)	2.62 (0.60)
Quick Learning (Range: 1 to 5, theoretical mean: 3)	2.15 (0.73)	2.13 (0.75)	2.04 (0.42)
Omniscient Authority (Range: 1 to 5, theoretical mean: 3)	3.33 (0.71)	3.28 (0.72)	3.17 (0.67)
Certain Knowledge (Range: -0.2 to 3.18, theoretical mean: 1.49)	0.91 (0.64)	0.94 (0.6)	1.05 (0.5)

According to EBI, the lower the score in a dimension, the more sophisticated the epistemic beliefs are. Comparing the observed means to the theoretical means, engineering students score lower than average (and hence have a higher sophistication level) for: simple knowledge, innate ability, quick learning, and certain knowledge. However, engineering students scored higher than average for on the omniscient authority dimension indicating they are less sophisticated. This suggests that students believe in the power and exclusiveness of being an authority, which may suggest feeling distanced from the instructor.

Based on comparisons to the theoretical mean, the students are more sophisticated in the simple knowledge dimension. This is a significant finding and a departure from the science education literature in that, even at the sophomore level, engineering students realize the importance of theory versus facts and are open to complex explanations.

3.2.4 Metacognitive Dimensions

The four metacognitive dimensions were measured using the inventory of O'Neil and Abedi (1996) (Given in Appendix C). The instrument consists of 20 statements, five statements per dimension. The students were asked to what extent they "exhibit" the statement on a scale from one to five (1=not at all, 5= at all times, conduct the task). Developed by the Stanford researchers, this inventory has been used for over 15 years. Subscale reliabilities reported for the instrument range from 0.82 to 0.87, and correlations to achievement were reported to range from 0.19 to 0.31.

Table 4 demonstrates the mean and standard deviations of the measured metacognitive levels for each student cohort.

Table 4. Means and standard deviations of modeling score and metacognitive ability

	Cohort I **Sophomore Fall** **mean (stdev)** **n=49**	**Cohort II** **Sophomore Spring** **mean (stdev)** **n=51**	**Cohort III** **Senior year Fall** **mean (stdev)** **n=32**
Awareness (Out of 25)	19.19 (2.14)	19.16 (2.17)	19.46 (2.28)
Self-Checking (Out of 25)	18.59 (2.60)	18.64 (2.55)	18.66 (2.88)
Cognitive Strategy (Out of 25)	18.46 (2.37)	18.41 (2.39)	18.70 (2.53)
Planning (Out of 25)	18.97 (2.51)	19.01 (2.53)	19.54 (2.51)

According to Table 4, we notice that cohort I students report feeling weakest in their *cognitive strategy*, the ability to use multiple techniques and strongest in their *awareness*. Despite the fact that it seems there is not much variability, the results were sensitive enough to measure the differences between these dimensions. The weakness in *cognitive strategy* can be explained through their lack of domain knowledge. The students are limited in their knowledge which prevents them to create multiple methods. Cohort II students also report a similar attitude. Finally, cohort III students seem to differ from the others by feeling the strongest in *planning* and weakest in *self-checking*. Also from the sophomore year to senior year, the students report increasing levels of metacognitive ability; however these changes are not significant.

Appendix D provides a table that demonstrates the correlations of the variables in the longitudinal study, averaged for the four time points.. According to the table, one would note that, in general, there is a moderate positive correlation between the stages of modeling, except for the validation and verification dimension, where the correlation is negative between some of the stages. The general positive trend of correlation among the variables points to modeling skill development occurring in multiple modeling stages together. We note that the correlations between self-efficacy, epistemology and metacognition are mostly small. This finding potentially justifies discriminant validity and the need to individually test the impact of these constructs on modeling skill development.

Another observation is the overall trend of negative correlations between the metacognitive dimensions and the epistemic beliefs. We note that negative epistemic beliefs imply a more naïve epistemology. The negative relationship indicates that those students who hold more sophisticated epistemic beliefs also tend to have higher metacognitive abilities. The relationship between self-efficacy and the other constructs do not suggest a direct relationship between these constructs. Note that in the testing of the paper, we make the self-efficacy variable a dummy that differentiates between high and self-efficacy, and the results are based on this categorization, as opposed to the self-efficacy variable itself.

One should note that in this study, we are not measuring the direct relationship between the variables given, but the impact of time and the relationship between these variables and change in modeling stages, when the impact of time is controlled for. In addition, the correlations, even when moderate, can be significant due to smaller sample size. Therefore, the correlations by themselves do not imply casual relationships; and one should be careful not to place much meaning on the correlation numbers.

3.2.5 Control Variables

We used GPA and Gender variables as a control in the experiment. A cumulative GPA data, measured the semester before the student took the exercises was plugged to control for the success of student overall. Gender and GPA differences in the correlates of modeling skills and epistemic beliefs were not a primary focus in this investigation but were examined for descriptive purposes. We found that cohort I had an average CGPA of 2.92 and age 19.8; cohort II had an average CGPA of 2.97 and age 20.04 and finally, cohort III had an average CGPA of 3.18 and age 21.6.

3.2.6 Interview Procedure

Interview responses included in this dissertation consist of transcribed interviews of ten sophomore (cohort II) and eight (cohort III) senior teams of engineering students of University of Pittsburgh, after each MEA. Some interviews were conducted with members of the teams separately, due to unavoidable occurrences like sickness or job interviews. This resulted in over 39 transcriptions. The students were paid for their participation in the interview, which was conducted as a team based interview (i.e., a single member to four members met with the interviewer at the same time). The interviews ranged from 40 to 90 min following the submission of each MEA. Teams from the first cohort were not interviewed, as the questions aimed to capture changes in students' self-assessed modeling abilities.

The interviewer followed an open-ended question session, based on a pre-determined protocol, as given in Table 5. The questions aimed at understanding students' background and modeling process. A few questions focused on students' modeling structure, others elicited knowledge related to the model and inquired about the behavioral mechanisms of modeling. Where needed, the interviewer asked participants for further clarifications to elicit participants' knowledge about statistics and engineering economics. In addition, several "what-if" questions were posed asking participants what would happen if their model was perturbed. All interviews were audio recorded and transcribed.

The coding of the interview, as well as the detailed descriptions of the student answers are provided in Study 4, section 7.2.1 in detail.

Table 5. Interview questions

Questions	Goal of the Question
Background	
1. Background information including name, year, the MEA to be talked about	Background information for the talk
Modeling Process	
2. Can you describe me the process of modeling this exercise? 2.1 What was your first intuition on how you can solve it? 2.2 Did you use analogies in solving the problem- were you able to make connections to some of your previous life experiences or class exercises?	Aimed at understanding the process of solving the MEA and the developed model, how the thinking changed, what the methods tried out that did not make it to the final report were, how the student got the idea on how to model the problem.
3. What did you think of the data? 3.1 Did you think the data was enough /adequate? 3.2 Did you look up similar problems before you solved this one? 3.3. Did you search for any information before working on the model? 3.4 What resources did you use to search for information/ data?	Understanding the students' review and evaluation of data, information search strategies, information resources

Table 5 (Continued)

4. What are some of the unknowns left in this problem? 4.1 Do you think you had enough information to solve this problem? 4.2 What were the variables in this problem- what you could manipulate? 4.3 What were some of the scenarios in which your analysis would differ?	Understanding student's conceptual modeling, assumptions and boundaries on the model, the variables assumed the restrictions and limitations on the model, scenarios considered.
5. What kind of a model did you use? 5.1 How did you decide the right / appropriate mathematical model? 5.2 Did you consider any other models?	Understanding the approach to decide and construct the mathematical model, alternative models considered.
6. How sure were you of your calculations- did you do anything to make sure your solution is error free? 6.1 What software did you use? 6.2 How did you decide what software to use? 6.3 Did you play around with the data / model to see if your results could change?	Understanding the effort put into carrying out the calculations, the method and tools including the software, and understanding why students prefer certain tools over the others. Understanding students' reaction to uncertainty, and sensitivity analysis habits.
7. Did you think about how your suggestions / particularly a wrong solution might affect people?	Understanding the interpretation of the numerical results.
8.1 How do you determine if you solved the right question? 8.2 How do you determine if you solved the problem right?	Understanding the validation and verification thinking.

Table 5 (Continued)

Other Questions	
9. Did you have a goal/ constraint in your mind before you started to work on the problem?	Understanding the main motivation of the student (e.g. getting a good grade, spending least amount of time, etc.)
10. 1 What do you think you gained from this experience? 10.2 Did you find the problem … [complex/ ambiguous/ difficult/ straightforward]? 10.3 Would you like to see other exercises like this? 10. 4 How motivated were you to work on this exercise?	Understanding whether the MEA made a change from students' point of view. Understanding the attitudes towards the problem itself.
11. 1How much guidance did you get from your own experiences when you were trying to decide on how to solve the problem? 11.2 Did you make any associations to how this problem can relate to your career when you were working on it?	Connections to real life and generalizability.
12.1 While solving the problem, did you use any drawings/ figures/ lists to help you solve the problem?	Understanding the extent and use of visual aids.
13.1 How would you solve this if you were given this problem in your sophomore /junior year? 13.2 What do you think you have learned over time? 13.3 Do you think some of your skills have deteriorated?	Understanding the changes in methodology, students' awareness of his/ her own progress, learning and skill acquisition

Table 5 (Continued)

14. Are you ready/ excited to be an engineer soon?	Understanding students' overall motivation to perform engineering functions.
15. How happy are you with your education here? 15.1 Do you think you gather the knowledge to handle this exercise?	Understanding students' perception of his education and knowledge
16. 1 What was your personal role in the solution process? 16. 2 How happy were you with your teamwork?	Understanding the teaming process of students

4.0 STUDY 1: IMPACT OF SELF-EFFICACY ON GROWTH OF MODELING

4.1 MOTIVATION

Self-efficacy is defined as personal judgments of one's capabilities to organize and execute courses of action to attain designated goals and has been shown to be a powerful predictor of performance in various learning settings (Bandura 1977, 1986, 1997). In this study, we extend the findings of self-efficacy to modeling, and investigate the impact of modeling self-efficacy as one social cognitive factor in helping to develop better modeling ability. The objective is to understand the short term and long term changes in modeling skills and the prediction power of self-efficacy in modeling. We achieve this objective through the use and analysis of special engineering modeling exercises called Model-eliciting activities (MEAs). In addition, this essay presents the implementation of a newly developed Engineering Modeling Self-efficacy Scale (EMSS).

Previous measurements of self-efficacy have employed proxies in the form of test scores, and assignment grades to generalize self-efficacy scales as overall self-efficacy. Conclusions from these measurements are that such self-efficacy "instruments" are not based on the concerned task, which, in turn, provide results in contrast to the true nature of self-efficacy beliefs; and thus carry less predictive value (Bandura 1997). Therefore, it is important to measure self-efficacy based on the task itself. Measurement examples to date, in engineering, exist for design self-efficacy (Carberry et al. 2010), tinkering self-efficacy (Baker, Krause and Purzer 2008, Richardson 2008), self-efficacy of engineering and computer use (Hutchinson et al. 2006, Marra and Bogue 2006, Amato-Henderson et al. 2007, Shull and Weiner 2002); as well as generalized self-efficacy in engineering instruments. To our knowledge, there are no self-efficacy instruments specific to engineering modeling.

For the "Engineering Modeling Self-efficacy Scale" (EMSS), we generate items of behavioral orientation that aim to measure the strength of engineering students' beliefs about their capabilities to accomplish modeling tasks. Building on Tsang's (1991) modeling stages, we created seven theoretical subscales within the EMSS and then tested for the latent factors that potentially explain the variation in modeling self-efficacy. Our analysis revealed seven dimensions that roughly correspond to Tsang's stages with high internal reliability. Following our item reduction and exploratory factor analysis, we demonstrate how the EMSS can be used to identify differences within varying engineering disciplines, academic year and gender. The findings suggest that self-efficacy beliefs are similar within disciplines, and, as expected, are higher for seniors compared to sophomore students, as well as for male engineering students. In addition, we discuss the predictability of this scale and its validity.

Our methodology further develops a theoretical argument on how and why the benefits of self-efficacy can translate into modeling. We discuss, in specific, the relationship between the use of MEAs and self-efficacy. Collecting data from sophomore and senior level engineering students, we show that self-efficacy impacts the growth of modeling abilities in engineering students. The differences in varying modeling abilities can be explained by varying self-efficacy levels, which is in itself a surprising finding. The rest of the study develops as follows. We provide a summary of the literature to help the reader understand the relationship between self-efficacy and modeling. We summarize the theoretical framework that shows the predicted effects of self-efficacy on engineering modeling outcomes; describe the data of the study, as well as how EMSS was used to measure engineering modeling self-efficacy. Next, we provide our findings, with implications and discussions. Finally, we give suggestions for practitioners and ideas for future research to the engineering education community.

4.2 BACKGROUND

4.2.1 Self-efficacy

An educational observation is that individuals with strong outcome expectations can have low perceived capabilities. For example, even when a student expects a good grade from an educational task, he can still carry doubts about how capable he is of doing it. Similarly, statements like ‘I have no idea how I got an A’ potentially point to differences in one’s beliefs and his external ability assessment.

The observations in differences of outcome expectations and one’s belief in his abilities was what led Bandura to define the concept of self-efficacy (Zimmerman and Schunk 2003). Self-efficacy is a person’s belief in his or her capability to successfully perform a certain task (Bandura 1986). Perceived self-efficacy helps to account for a wide variety of individual behaviors, including: changes in coping behavior (Bandura 1982), levels of physiological stress reactions (O'Leary 1992), self-regulation (Schunk and Zimmerman 1994), achievement strivings (Bandura 1982), growth of intrinsic interest (Bandura and Schunk 1981), choice of career pursuits (Hackett and Betz 1989), choice of majors in college, success in course work, and perseverance (Hackett and Betz 1989; Lent, Brown, and Larkin, 1984).

In addition to having high predictive power, self-efficacy is also known to increase performance, such as improvements in assumptions (Bandura 1977) and strategies or reacting less defensively when negative feedback is received (Heslin and Klehe 2006). In contrast, low self-efficacy can lead to erratic analytic thinking that undermines the quality of problem solving (Wood and Bandura 1989), which can result in poor modeling outcomes. Students with low self-efficacy tend to blame either the situation or another person when things go wrong (Heslin and Klehe 2006). For example, an individual's reaction to a low grade on an exam is manifested by blaming the instructor's ability to teach. Denial of responsibility for poor performance inhibits one's chances to learn how to perform more effectively in the future.

To understand the construct of self-efficacy, it is important to note its distinctive characteristics, particularly the difference between self-efficacy, self-confidence and self-esteem (Pajares 2006). Self-confidence is defined as the general personality trait that relates to how confidently people feel and act in most situations and self-esteem is the extent to which a person likes himself. Self-efficacy is a task specific characteristics and it is generally also more readily developed than self-confidence or self-esteem. Self-efficacy has also been shown to be a stronger predictor of how effectively people will perform a given task than self-confidence or self-esteem. Self-efficacy is task specific, implying that people may simultaneously have high self-efficacy for some tasks and low self-efficacy for others.

Self-efficacy beliefs are measured in a task-specific manner, thus there is no single standardized measure for self-efficacy. Such measures are developed to assess capacity to either achieve a certain outcome on a particular task or engage in the processes likely to lead to a certain desired outcome. The items in EMSS are geared towards measuring process self-efficacy - aiming to be informative, predictive, and useful for addressing areas where self-efficacy influences specific modeling behaviors, tasks, or objectives (Yildirim, Besterfield-Sacre, Shuman 2010a).

4.2.2 Self-efficacy Measurement in the Literature

The instruments that have been developed to measure self-efficacy in a variety of domains range in their generalizability and content. In educational environments, measurements of self-efficacy can be conducted using a test, or the student's grade at the end of a course. Measurements have also been conducted using self-efficacy scales that do not refer to any specific domain. Such global measures refer to general competence with items related to 'accomplishing goals in general' and 'performing effectively on different tasks' (e.g., Chen, Gully, and Eden, 2001; Scholz, Gutiérrez-Doña, Sud, and Schwarzer, 2002).

Several overall self-efficacy scales have been created, under the heading 'general self-efficacy'. These scales intend to measure belief in one's overall competence or perception of one's ability to perform across a variety of different situations (Judge, Erez and Bono 1998). Measurement of general self-efficacy is in direct contrast with the task-dependent nature of self-efficacy and most carry low predictive value (Bandura 1997). In Bandura's (2006) resource for researchers interested in creating self-efficacy scales, he confirms that an all-purpose self-efficacy measure is likely to fail because the items in such scales may have little or no relevance to the domain of functioning. He suggests instead that proper self-efficacy measurement must be tailored to a specific domain and tasks in which individuals can differ in their success rates and beliefs about their success rates. Pajares (1996) provides a comprehensive list of previously constructed self-efficacy scales for academic settings. We used a combination of this list and more recently added scales to create a comparison list for our instrument. This list is provided in Table 6.

Table 6. List of various self-efficacy scales

Source	**Sample Question or Direction**	**Answer Options**
Teaching Efficacy (Bandura 1993)	*How much can you influence the decisions that are made in your school? (Completed by various teaching related tasks)*	*1-9 scale with 1=lowest*
Mathematics problem solving self-efficacy (Pajares and Miller 1995)	*How confident are you that you that you would give the correct answer to the following problem without using a calculator…? [a sample math problem]*	*1-6 scale with 1=lowest*
Self-Efficacy for self-regulated learning (Bandura 1989)	*How well can you …? (completed by 11 self regulatory tasks)*	*1-7 scale with 1=lowest*
Self-efficacy for writing skills (Shell, Murphy, Bruning 1989)	*How confident are you that you can perform each of the following skills? (8 skills presented-e.g., "correctly spell all words in a one-page passage")*	*Scale of 0 to 100*
Mathematics courses self-efficacy (Betz and Hackett 1983)	*How much confidence do you have that you could complete the following course with a final grade of B or better?*	*0 to 9 scale*

Table 6 (Continued)

Collective efficacy (Bandura 1993)	*Please indicate your confidence that you can attain the following gains with the students in your class this year. [gains in 2-month presented]*	*0 to 10 scale*
Self-efficacy for performance division problems (Schunk 1981)	*[Division problem shown for 2 seconds] Circle the number on the matches how sure you are that you could work problems like those shown and get the right answers.*	*Scale of 10 to 100- in intervals of 10*
Self-efficacy for reading tasks (Shell, Colvin, Bruning 1995)	*How confident are you that you can perform each of the following tasks? (18 tasks presented-e.g., "read a letter from a friend")*	*1 to 5 scale*
Self-efficacy for academic achievement (Bandura 1989)	*How well can you .? completed by 9 academic domains-e.g. general mathematics, learn reading and writing language skills*	*1 to 7 scale*
Self-efficacy for learning (Schunk 1996)	*Students are presented with sample mathematics problems or reading/ writing tasks for a brief time. They are asked to provide a confidence judgment to correctly solve the problems, perform paragraph writing tasks, etc.]*	*Scale of 10 to 100- in intervals of 10*
Carberry et al. (2010)	*Students are presented with engineering design tasks and are asked how confident they feel in accomplishing the tasks*	*Scale of 10 to 100- in intervals of 10*

An investigation of these scales reveals some notable generalizations. First, as shown in the table, all the scales are domain specific and serve distinct purposes; and each is created to measure self-efficacy of a certain academic task. Hence, we surmise that if one wishes to measure students' abilities in engineering modeling, a scale distinct from the existing scales should be constructed. Second, almost all academic self-efficacy scales include a measurement of a task by providing immediate examples or a measurement context (i.e., they provide material for measuring the task). For example, to measure self-efficacy in reading, students are asked to read a text; in the case of writing self-efficacy, they are asked to write one. Thus, we conclude that to measure self-efficacy of modeling, a relevant modeling task should be given to the students along with the instrument. Third, there is no agreement on a universal measurement scale (i.e., some researchers use a 0-100 interval scale; others prefer a Likert type scale). Bandura (2006) indicates a 0-100 interval is indeed beneficial; however, current scales available in the literature do not necessarily adhere to this suggestion. For our EMSS we utilized a one to five point rating scale since it better suited to the context of our overall study.

A particularly relevant self-efficacy scale to engineering modeling is the engineering design self-efficacy scale (EDSS) constructed by Carberry et al. (2010). This scale provides a suitable benchmark for comparison for several reasons. First, it is created for measuring self-efficacy of engineers in the relevant concept of engineering; i.e., design. Design of a system or component includes modeling abilities as well as problem solving skills. Second, this scale is relatively new, ensuring that certain problems with older self-efficacy scales have not been repeated.

We have constructed the EMSS based on the modeling stage descriptions and subtasks that are listed by Tsang (1991). We note that the process of engineering modeling looks different than mathematical modeling, but we argue that mathematical modeling appropriately corresponds to the engineering modeling steps through the development of calculation models, carrying out modeling calculations and sensitivity analysis, and results evaluation. Therefore, we make the assumption that mathematical modeling is a subset of engineering modeling.

4.3 THEORY

4.3.1 Impact of Self-efficacy on Modeling

A rich stream of studies related to self-efficacy and academic outcomes have been conducted in the domain of mathematics (Hackett and Betz 1989, Lent, Brown, and Gore 1997), reading, and writing (Shell, Colvin, and Bruning, 1995, Shell, Murphy, and Bruning, 1989). Based on the literature on self-efficacy and academic achievements, we describe how and why one can expect the self-efficacy beliefs to influence modeling outcomes.

We summarize the findings on self-efficacy in the educational literature and discuss how and why self-efficacy is expected to influence the modeling outcomes. Figure 11 lists those mechanisms that are likely to influence modeling outcomes; namely, effort, strategy, learning, emotional and social pressure, self-regulation, goal setting and metacognition. Each of these effects is described in detail next.

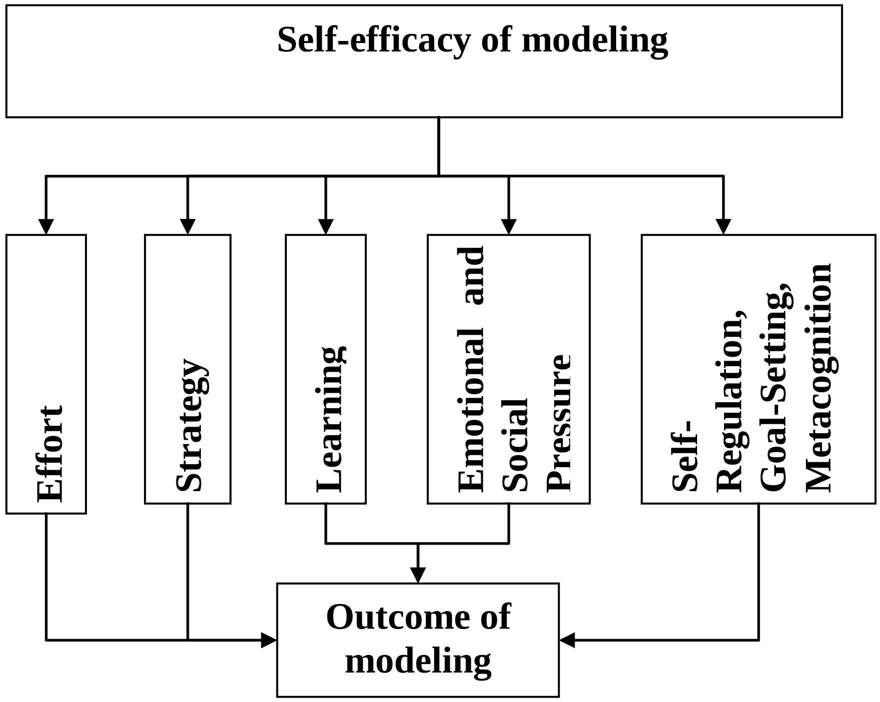

Figure 11. Consequences of self-efficacy expected to influence modeling

The impact of self-efficacy on the outcome is noted to be bidirectional (Paunonen and Hong 2010) implying that it is possible for the difference in the outcome of two students with different levels of self-efficacy to result from (i) the student with higher self-efficacy doing better than expected, (ii) the student with low self-efficacy doing worse than expected, or (iii) both. However, studies often only investigate the direction where high-self-efficacy levels are assumed to result in higher outcomes.

4.3.1.1 Effort

Self-efficacy influences students' skill acquisition by increasing their persistence (Schunk 1981); and self-efficacious students participate more readily, work harder, persist longer (Bandura 1997). Further, self-efficacy for learning correlates positively with students' rate of solution of arithmetic problems (Schunk, Hanson, and Cox 1987; Schunk and Hanson 1985). Salomon (1984) found that self-efficacy is positively related to self-rated mental effort and achievement during students' learning from text material that was perceived as difficult. This influence on perseverance is likely to suggest that higher self-efficacy helps students in cases of complex modeling problems. How much effort people will expend on a task, as well as, how long they will persist when they face difficult situations is also influenced by self-efficacy (Bandura 1977). Modeling exercises can pose a challenge to the students since they are often open-ended and involve complex analysis, as well as mathematical competency. If students have higher self-efficacy, they are likely to spend more effort on a modeling task even if it is challenging. As a result, such students have better coping strategies, resulting in better outcomes than what their abilities alone would permit.

4.3.1.2 Strategy

Another mechanism influencing modeling is the choice of activities and strategies involved. Self-efficacious students have been shown to undertake difficult and challenging tasks more readily than do inefficacious students. Bandura and Schunk (1981) found that students' mathematical self-efficacy beliefs were predictive of their choice of arithmetic activity to engage in. Modeling is an open-ended task, which can possibly be addressed by different sets of mathematical representations. Students' self-efficacy can influence the choice and complexity of mathematical model and thereby influence the engineering model. For example, a student who foresees two possible mathematical representations of an engineering model may choose the more challenging one if he is more efficacious. This effect is particularly situated for MEA implementations, because they allow students to create their own models. Students with higher self-efficacy might be more inclined towards trying new or more complicated models or discovering concepts on their own. In other words, the discoverer role's success of MEAs (Yildirim, Shuman, Besterfield-Sacre 2010b) can depend on the self-efficacy level of the student.

4.3.1.3 Learning

Zimmerman and Kitsantas (1996) found students' interest in learning and writing revision to be highly correlated to self-efficacy and writing revision is linked to MEAs. Further, engineering models are created through some symbolic or formal language; and these languages can take the form of concepts, figures, mathematical symbols, spoken language, or computer codes. In documenting a model, revision can help to eliminate errors, repetitions, redundancies as well as improve details. Therefore, self-efficacy, can through its effect on writing revision improve a student's modeling outcome.

4.3.1.4 Emotional and Social Pressure

There is thus an emotional link to self-efficacy through stress, anxiety, and depression (Bandura 1997). Students can prefer to convey a positive image to others by expressing strong self-efficacy beliefs and they can become anxious or depressed when they perceive themselves as untalented. Low self-efficacy can be distressing, preventing even gifted students from effectively performing. This, in turn, influences their ability to learn and to cope more effectively with the challenges. For example, Pajares and Kranzler (1995) studied the relationship between self-efficacy and students' anxiety reactions regarding mathematics, and found that self-efficacy was predictive of mathematics performance. Similarly, Siegel, Galassi, and Ware (1985) found that self-efficacy beliefs were predictive of mathematics performance, in relationship to mathematics anxiety.

4.3.1.5 Self-Regulation, Goal-Setting, Metacognition

Self-efficacy influences a student's self-regulation and goal setting. Zimmerman, Bandura, and Martinez-Pons (1992) found that the more capable students judged themselves to be, the more challenging the goals they embraced. Zimmerman and Bandura (1994) demonstrated that self-efficacy beliefs and goal setting significantly add to the predictability of the relationship between self-efficacy and achievement.

Self-efficacy has been shown to influence metacognitive skills of students, in particular through the dimensions of self-monitoring during concept learning (Bouffard-Bouchard, Parent, and Larivee, 1991). Efficacious students were better at monitoring their working time, more persistent, less likely to prematurely reject correct hypotheses, and better at solving conceptual problems than inefficacious students of equal ability. Overall, there are multiple ways in which students' self-efficacy for modeling can influence their modeling outcome. Based on which mechanism(s) is active, self-efficacy can be a direct (main) effect, or an indirect (moderation effect), or both. Using grounded theory approach, we explore in subsequent sections the influence of self-efficacy on separate modeling outcomes by testing for main and moderation effects.

4.3.2 MEAs and Modeling Self-efficacy

One's self-efficacy levels can be expected to show in modeling exercises such as MEAs. The main three major antecedents to self-efficacy (Staples, Hulland and Higgins 1999); enactive self-mastery, vicarious experience, verbal persuasion can all be observed while implementing an MEA. We explain each source and discuss how a MEA educational environment can help develop self-efficacy via these sources.

When working on a MEA, students have minimal guidance from their instructors, and they rely heavily on their own abilities. They work on these exercises in and out of class with a small team or individually; hence, the MEA acts like an unguided discovery situation potentially maximizing students' self-efficacy with respect to working on their own or within a team.

4.3.2.1 Enactive self-mastery

Enactive self-mastery is achieved when people successfully perform a task. The student is convinced that he has what it takes to build a model, upon successfully accomplishing the assigned tasks. Gradually escalating the difficulty of tasks helps students to increase the effect of self-mastery, i.e., breaking down tasks into small steps that are relatively easy, ensuring a high level of initial success (Heslin and Klehe 2006).

MEAs can be instrumental in achieving enactive self-mastery, when (i) implementation follows a gradual increase in task difficulty, and (ii) achievements of students on challenging tasks are celebrated. If these conditions are met, repeated MEA experience can develop enactive self-mastery in modeling (as well as working in a team and writing reports) and likely contribute to modeling performance.

4.3.2.2 Vicarious experience or role modeling

Vicarious experience or role modeling becomes a source of self-efficacy when a student observes another student perform and accomplish a task. Heslin and Klehe (2006) suggests that vicarious experiences are more effective in raising self-efficacy levels when the person observed is liked and has similar characteristics (e.g., age, gender, and ethnicity) to the person observing them. In other words, a student who observes his friend of the same gender, knowledge level, age etc. conducting the tasks, can be inspired to persist. An anecdotal example of this observation is where students suggest they learn better in the recitation in which a (senior) fellow student is responsible for the teaching, rather than the instructor.

In an educational environment where MEAs are implemented, a student's team members as well as the instructor can become an effective role model by demonstrating to team members it is possible. To successfully achieve role modeling effect, first, MEA implementations can follow mentoring and feedback to expose the student to role models. Second, students can be teamed up with students they like and are similar to. This way, students can learn from observing the successes and failures of others.

4.3.2.3 Verbal persuasion

A third source of self-efficacy is verbal persuasion; by a person who is often respected and influential, convincing another that he can perform the tasks successfully. It is not uncommon for students to perform better following a praise or encouragement from an instructor (Heslin and Klehe 2006). Verbal persuasion has also been shown to have a significant influence even in the form of positive self-talk. Repetition of student's will and desire to perform can help to increase levels of self-efficacy.

Verbal persuasion by another person is more likely to boost self-efficacy when it is coming from a credible source, and when it focuses on success resulting from devoting effort to mastering acquirable skills, rather than an inherent talent (Heslin and Klehe 2006). When instructors emphasize the importance of effort and persistence in achievements, and match their verbal recommendations with their behavior, students are more likely to be encouraged.

Conflicts with the verbal persuasion occur when students are told they are capable of a modeling task, but then the assigned case is too advanced for their knowledge level; hence, wearing down both the students' self-efficacy and the instructor's credibility. Bandura (1986) suggests, where applicable, having students develop a progress chart prior to complimenting them on their genuine progress as a way of raising their sense of what they can achieve.

4.4 CREATION AND TESTING OF EMSS

Our approach for testing the impact of modeling self-efficacy on students' ability to model was divided into two phases. In the first phase, we derived a scale to measure modeling self-efficacy. During this phase, testing of the instrument for reliability and validity was primarily exploratory, with the main purpose being to assess the reliability of the projected scale and to gather data to further refine the items into a finalized instrument. In the second phase, we investigated the dimensions of engineering modeling self-efficacy for two engineering disciplines, and subsequently tested the reliability and validity of the items. Based on the self-efficacy literature, we expected that the self-efficacy scale would likely have latent factors (dimensions) apart from the observable stages of modeling tasks.

4.4.1 Test Data Collection

The respondents took the EMSS for course credit and/ or monetary compensation. The sample included a total of 180 students (22% female, which is proportional to the engineering student body), sophomores and seniors, at the University of Pittsburgh during the 2009-2010 academic year. Forty-nine percent were majoring in industrial engineering, and fifty-two percent were in civil engineering. The majority of the respondents (82%) were between the ages of 18 and 22 years; 10% of the respondents were between the ages 23 to 27 years; and 3% were between 28 and 32. The students' ethnicity was not reported as part of this research work, but ethnicity is proportional to the engineering student body at the University of Pittsburgh. Further, all subjects were fluent in English. Surveys were administered via paper and pen to the civil students and through a web-based surveying tool to the industrial engineering students. Proper human subjects' clearance was obtained for this research and for this publication.

4.4.2 Item Generation

To build our self-efficacy scale, we followed two guiding sources: (1) we investigated relevant scales in engineering and fields that are closely related to engineering modeling and (2) we observed Bandura's (2006) suggested guidelines. We defined specific performance tasks that directly related to engineering modeling as the targets of our subjects' self-efficacy ratings, and then we tested this scale with many engineering students from two engineering sub-domains.

Subtasks of the modeling process were identified and listed based on Tsang's definitions for the modeling processes creating a large pool of potential scale items. This initial list of over 60 items was reduced through combination and elimination, to minimize redundancy while maximizing coverage of the modeling context. To derive the final list, items were pilot tested through in-depth interviews conducted with student teams. Multiple task-oriented statements were developed similar to the engineering design self-efficacy scale of Carberry et al. (2010).

The resultant 36 item instrument (seven modeling stages times five to six items per stage) is provided in Appendix A. Each item and the specific tasks that are covered are given in Figure 12.

Items	Related modeling stage	ITEMS OF EMSS – Description
1-6	Review and evaluation of data (RED)	• Deciding what data is necessary to test and evaluate a model, • Searching a database to find data to use in a model, and finding exemplary models to use as a starting point, • Determining whether the data on hand or found from the literature is representative of the entire system, whether the data is reliable or the sample size is sufficiently large, relevant to the model. Managing missing data where needed.
7-13	Conceptual modeling & potential scenarios (CON)	• Developing a schematic representation of the system, • Identifying (e.g. Physical, biological or chemical) processes involved in the system, and specifying inputs and outputs of the system, exploring relationships between the processes within the system (creating the conceptual model), • Deciding external conditions that can influence the system, necessary conditions for a system to exist or function normally, and extreme cases of how the system functions.
14-16	Establishment of performance criteria (EPS)	• Deciding what is to be measured quantitatively using the model (referred to as the performance criteria) and determining how to improve upon the performance criteria.
17 – 22	Development of calculational models (CAL)	• Developing calculational or computational models to estimate the performance criteria, identifying the constraints, boundary conditions, etc. • Writing a computer program, or hand calculations.
23 – 27	Calculations, sensitivity analysis (CUS)	• Carrying out the actual calculations, • Determining reliability and error in calculations, • Sensitivity analysis
28 – 32	Results evaluation (RE)	• Transfer of the numerically found results back to qualitative information, and interpretation of the results
33 – 36	Validation/ verification (VV)	• Validation and verification of the overall model results

Figure 12. Items of EMSS

The instructions asked students to rate how well they think they can perform each of the tasks listed in the items via a five-point rating scale ranging from “Cannot Do at All” to Can Do Very Well”. The order of items was randomized within each modeling stage. Additionally, the survey asked students to provide basic demographic information including gender, age, major, and year in school.

4.4.3 Item Reduction and Factor Analysis

The first phase of scale testing was for internal consistency. Using the 36 items, a Cronbach’s alpha of 0.94 was calculated for the entire instrument, as measured in SAS Software (version 9.2). A factor analysis using maximum likelihood estimation and varimax rotation resulted in a solution with eight factors having eigenvalues higher than 1.00. Using a conservative minimum factor loading of 0.40 or higher, we eliminated one factor to arrive at seven dimensions that properly correspond to the seven theoretical subscales. Nine of the original 36 items in the pool were eliminated completely from the analysis because their factor loadings were less than 0.40. Two items cross-loaded on more than one factor, but were included in the analysis. The remaining items were tested using a minimum gap of 0.10 between salient coefficients to confirm that each item loaded on a single factor (Nunnally 1978). The overall reliability of the remaining items was 0.90. These remaining items and the factors they load are given in Table 7. In the case of the two items that cross-loaded more than one factor (items 20 and 28), the higher loading factor was chosen.

Table 7. Loadings of EMSS items on factors

Loadings of the Items on Factors									
Item No	**Tsnag's modeling dimension**	**ITEM**	**Factor 1**	**Factor2**	**Factor3**	**Factor4**	**Factor5**	**Factor6**	**Factor7**
1	RED	Decide what data is necessary to use in the model.	**.40**						
3	RED	Determine whether the collected/given data sample is representative of the population.	**.64**						
4	RED	Decide whether the data is reliable and sample size is large enough.	**.58**						
8	CON	List the sub-processes within the system (e.g. physical, biological, and/or chemical, economical relationships, etc.)		**.54**					
9	CON	Identify the relationships between sub-processes (how changes in one affect changes another).		**.66**					
17	CAL	Quantify the impact of sub-processes on the performance criteria (goal of the model).		**.50**					
18	CAL	Simplify the relationships between processes that exist in the system.		**.50**					
10	CON	Identify inputs and outputs of the system.			**.64**				
11	CON	Determine the (initial and boundary) conditions for the system to start/ stop functioning.			**.64**				
12	CON	Determine the necessary conditions for a system to exist/ survive once started functioning.			**.52**				
13	CON	Predict how the system will function in extreme cases.			**.46**				
14	EPS	Determine the criteria to decide if the model performs well.				**.70**			
15	EPS	Determine whether the performance criteria chosen are appropriate for the system.				**.65**			
16	EPS	Find ways to modify the performance criteria to make it better.				**.66**			
19	CAL	Identify the variables and parameters in a model.					**.56**		
20	CAL	Identify the constraints on the model.			.47		**.41**		

Table 7 (Continued)

28	RE	Understand/ evaluate the results of a calculational model					**.56**		.42
32	RE	Explain how the results of a calculational model are obtained.					**.73**		
33	VV	Determine qualitatively if the developed model looks ‘alright’.					**.61**		
34	VV	Determine numerically if the model results are valid.					**.61**		
21	CAL	Write a computer program to calculate the outcomes of the model.						**.77**	
22	CAL	Choose a mathematical/ statistical model to calculate the performance criteria/ results of a developed model.						**.60**	
24	CUS	Calculate the outcomes of the model using a computer code.						**.70**	
26	CUS	Determine the uncertainty in the parameters and data.							**.54**
27	CUS	Conduct a sensitivity analysis on the numerical results.							**.57**
35	VV	Determine ways to measure if the created model generates results in line with the actual system.							**.68**
36	VV	Determine how the model developed compares to other models of the same system.							**.69**

An analysis of factors reveals that they are comparable to the seven latent dimensions of engineering modeling. Accordingly, three of the factors directly map to the theoretical modeling stages listed by Tsang; namely, Review and Evaluation of Data (RED), Development of Conceptual Model (CON), and Establishment of Performance Criteria (EPS).

The remaining four factors are reasonable combinations of Tsang’s stages; enabling us to examine how students actually group certain modeling tasks together compared to how it is hypothesized in the literature. For example, Factor 2 is a combination of Conceptual Model

Development (CON) and Development of Calculational Model (CAL) tasks; however, the common threads are those items related to understanding the sub-processes within a system. The students are evaluating the relationships within a system, and thus we call this factor, "Process Modeling". Factor 5, includes items from Creation of a Calculational Model (CAL), Results Evaluation (RE) and Validation and Verification (VV). The items within this factor are about understanding the model and explaining it; hence, this dimension is labeled "Interpretation". Factor 6 is a combination of items from Development of Calculation Model (CAL) and Carrying out Calculational model (CUS) stages. We certainly recognize that students may look upon Developing a Calculational Model (CAL) and Carrying out Calculational Models (CUS) as compliments; hence this dimension is labeled as "Calculational Modeling". Finally, the seventh factor involves items from both Carrying out Calculational Models (CUS) and Validation and Verification (VV). The items are relevant to sensitivity analysis (CUS) and Validation and Verification (VV), implying that sensitivity analysis is also considered as a way of validation in students' minds. They form a dimension together; resulting in the label "Uncertainty and Validation."

Internal reliability for each dimension is reported in Table 8. All results for Cronbach's alpha were between 0.6 and 0.9, supporting the argument that within each dimension the responses of students were reliable.

Table 8. The dimensions of engineering modeling self-efficacy

DIMENSION	Factor No	Items	Reliability
Review and Evaluation of Data	1	1,3,4	0.61
Process Modeling	2	8,9,17,18	0.74
Conceptual Modeling & Potential Scenarios	3	10-13	0.82
Establishment of Performance Criteria	4	14-16	0.81
Interpretation	5	19,20,28,32-34	0.84
Calculational Modeling	6	21,22,24	0.74
Uncertainty and Validation	7	26,27,35,36	0.84

The internal consistency tables shows the values for each of the dimensions of self-efficacy. This table presents the inter-correlations, where the diagonal element is the square root of the average variance extracted. This table can be used to assess the discriminant validity of the constructs.

Table 9. Internal consistency of EMSS factors

Internal Consistency of the Constructs

Modeling Self-efficacy Dimension (Notation)	Number of Items	Internal Consistency	Cronbach's Alpha	Average Variance Extracted
Review and Evaluation of Data Self-efficacy (SE_{RED})	3	.69	.76	.35
Process Modeling Self-efficacy (SE_{PM})	4	.84	.74	.52
Conceptual Modeling & Potential Scenarios Self-efficacy (SE_{CON})	4	.69	.74	.35
Establishment of Performance Criteria Self-efficacy (SE_{EPS})	3	.59	.77	.48
Interpretation and Evaluation Self-efficacy (SE_{IE})	6	.66	.68	.71
Calculational Model Self-efficacy (SE_{CAL})	3	.83	.78	.50
Uncertainty and Validation Self-efficacy (SE_{UV})	4	.85	.69	.61

According to this table, the reliability and validity of all factors were acceptable. Two factors (i.e., Interpretation and Evaluation, and Uncertainty and Validation) had lower Cronbach's alpha scores and acceptable internal consistency values similar to Staples, Hulland and Higgins (1999). The Cronbach's alpha for the 36 items which were used to construct the single score was 0.9, indicating strong internal consistency.

Table 10. Discriminant validity analysis

Discriminant Validity Analysis

Modeling Self-efficacy Dimensions	**1.**	**2.**	**3.**	**4.**	**5.**	**6.**	**7.**
1. Review and Evaluation of Data Self-efficacy (SE_{RED})	**.59**						
2. Process Modeling Self-efficacy (SE_{PM})	.14	**.72**					
3. Conceptual Modeling & Potential Scenarios Self-efficacy (SE_{CON})	.16	.27	**.59**				
4. Establishment of Performance Criteria Self-efficacy (SE_{EPS})	.30	.34	.31	**.69**			
5. Interpretation and Evaluation Self-efficacy (SE_{IE})	.39	.55	.29	.49	**.84**		
6. Calculational Model Self-efficacy (SE_{CAL})	.05	.01	.18	.12	.19	**.71**	
7. Uncertainty and Validation Self-efficacy (SE_{UV})	.24	.39	.55	.38	.64	.16	**.78**

The bold diagonal elements are the square root of the variance shared between the constructs and their measures (i.e., the average variance extracted). Off diagonal elements are the correlations between constructs. For discriminant validity, the diagonal elements should be larger than any other corresponding row or column entry. This can be seen by examining the correlations among the two factors and the square root of the average variance extracted. An examination of table shows that the discriminant validity was relatively weaker between Uncertainty and Validation factor and Interpretation and Evaluation factor (0.64), indicating that the two constructs are closely inter-related. Since this correlation (0.64) does not exceed the average variance extracted (0.78/ 0.84), there is a still able to claim proper discriminant validity between the modeling self-efficacy factors. The correlations with other constructs were generally low implying adequate discriminant validity.

4.4.4 Characteristics of EMSS

It is important to note the converging and diverging characteristics of a scale during its development. Several characteristics of the EMSS are consistent with other scales. Both the EDSS and EMSS have a behavioral focus utilizing student tasks from the literature. Therefore, according to Bandura (2006)'s *generality* dimension, they are both limited to the respective domains of their interest (design and modeling, respectively), but also generalizable to different design and modeling tasks. This suggests it is consistent with our aim to make the scale comprehensive and applicable to all engineering disciplines. In addition, in regards to the *strength* of self-efficacy, both scales pose questions that aim to measure the confidence of student about herself.

Among the characteristics that differentiate the EMSS from other scales; our statements attempt to uniquely represent specific modeling tasks compared to other more general self-efficacy scales previously developed. Note that certain items violate the rule to avoid compound statements, where respondents might agree with one part but disagree with a second part. Although we edited the items to make them as elemental as possible, it became clear that certain theoretical perspectives could not be adequately represented with a single clause. Compound statements were employed only when deemed necessary. Finally, most items are written in the "positive" direction for a subscale (i.e., agreement with an item indicates endorsement of that subscale perspective), whereas traditional methods of scale construction call for balancing positive and negative items. The decision to do this was made intentionally, as initial attempts to change some subscale items to negative tended both to change the meaning of the item and to make it fit more appropriately with different subscales. Extent of agreement with items was graded rather than dichotomous response scales (i.e., agree or not agree) and different respondents to the scale would find different items positive and negative. Therefore, the danger of positive or negative response set affecting the results seemed greatly reduced.

4.5 ANALYSIS

4.5.1 Analysis of Sophomore Year Change

A growth curve analysis was used to examine changes during the sophomore year. Primary hypotheses were tested using multilevel models that included both random and fixed effects (Singer 2002), using full maximum likelihood estimation, through SAS statistical package, Version 9.2 (Littell, Milliken, Stroup and Wolfinger 1996). The analyses consisted of two levels; between-subjects factors and within-subject factors, on linear and quadratic changes in growth of modeling skills. We conducted exploratory analyses specifying our models with alternative error covariance matrix structures. Model fit was strongest with an unstructured covariance matrix; therefore an unstructured error covariance matrix was specified for the models (Long and Pellegrini 2003).

4.5.1.1 Unconditional Models: Means and Growth Models

To describe and partition the modeling skill development variation, an unconditional means model was built. We estimated a two-level model not including any predictors, which takes the following form:

Level 1: $$Y_{ijk} = \beta_{0jk} + e_{ijk},$$

Level 2: $$\beta_{0jk} = \gamma_{00k} + \delta_{0jk},$$

where *k=1,2,…7* stands respectively for each of the modeling outcome measures, RED, CON, EPS, CAL, CUS, RE and VV. We remind the reader that these outcomes are the grades obtained from the modeling grading sheet; not the theoretical self-efficacy factor scores obtained from EMSS. In this model, the dependent variable, Y_{ijk}, the i^{th} month modeling skill level of the j^{th} student for the k^{th} modeling factor, is a linear function of a grand mean (γ_{00k}), a deviation of the j^{th} student from the grand mean (δ_{0jk}), and a random error term associated with the skill level of the i^{th} month of the j^{th} student (e_{ijk}). The model separates the variation of modeling skill development into variation between student means (τ_{00k}), and variation among month within the students ($\sigma^2{}_k$) (Singer 1998). Unconditional models for each outcome are shown in Table 11. The intercepts at Table 11 demonstrate the overall score of a sophomore student on each modeling outcome four months after the semester (i.e., after one semester). Note that an overall list of the various models tested is provided in Appendix E, for self-efficacy, epistemology, and metacognition.

Table 11. Unconditional means model for modeling growth of sophomores

Unconditional Means Models Longitudinal Growth in Modeling- Sophomore Year

Predictors	RED	CON	EPS	CAL	CUS	RE	VV
	Est. (std.err)	**Est. (std.err)**	**Est. (std.err)**	**Est. (std.err)**	**Est. (std.err)**	**Est. (std.err)**	**Est. (std.err)**
Intercept	3.39 (0.08)***	3.08 (0.07)***	3.43 (0.09)***	3.05 (0.11)***	2.84 (0.09)***	2.66 (0.08)***	0.68 (0.09)***
Fit Statistics							
-2 Log Likelihood	598.6	608.5	606.2	691.8	598.0	605.6	634.3

***denotes p<0.01; **denotes p<.05; *denotes p < 0.10. Sample size, n=39 with four time periods.

Following the means model, we then introduced the time variable (i.e., months) and fitted an unconditional linear growth model. The level 1 equation estimates the individual student's trajectory of modeling growth (β_{1j}) in addition to the mean (β_{0j}). The level 2 equation simultaneously partitions the two estimates into sample averages and error components.

Level 1: $$Y_{ijk} = \beta_{0jk} + \beta_{1kj} Month_{ijk} + e_{ijk},$$

Level 2: $$\beta_{0jk} = \gamma_{00k} + \delta_{0jk},$$

$$\beta_{1jk} = \gamma_{10k} + \delta_{1jk},$$

where *k=1,2,…7* stands respectively for each modeling outcome grade for RED, CON, EPS, CAL, CUS, RE and VV.

The month variable ranges from one to eight and represents the number of months since the sophomore semester started. This variable was mean-centered; thus, the intercept of the model reflects the modeling level of a student midway through the eight months. The SAS Proc Mixed procedure generated the results given in Table 12.

Table 12. Unconditional linear growth on modeling for sophomores

Unconditional Linear Growth Models - Sophomore Year

Predictors	**RED**	**CON**	**EPS**	**CAL**	**CUS**	**RE**	**VV**
	Est. (std.err)	**Est. (std.err)**	**Est. (std.err)**	**Est. (std.err)**	**Est. (std.err)**	**Est. (std.err)**	**Est. (std.err)**
Intercept	3.41 (0.07)***	3.09(0.07)***	3.45(0.08)***	3.07(0.11)***	2.88(0.08)***	2.68(0.07)***	0.68(0.09)***
Month	0.25(0.03)****	0.22(0.03)***	0.21(0.03)***	0.24(0.04)***	0.25(0.03)***	0.25(0.03)***	0.17(0.03)***
Fit Statistics							
-2 Log Likelihood	543.1	568.4	563.5	659.6	546.8	543.1	614.5
Incremental Chi-Square	56.5	40.1	42.7	32.2	51.2	62.5	19.8
Incr. degree of freedom	1	1	1	1	1	1	1
P-Value	p<0.001	p<0.001	p<0.001	p<0.001	p<0.001	p<0.001	p<0.001

***denotes p<0.01; **denotes p<.05; *denotes p < 0.10.

To improve the growth analysis further, a nonlinear model was tested by adding a quadratic term (the squared mean-centered months). As shown in Table 13, the results support a nonlinear growth model. Compared to the unconditional linear growth model, the unconditional nonlinear growth model was significantly better based on the incremental chi-square criterion, given in the fit statistics. In addition, intercept, linear and quadratic time variables were all significant at the 0.05 level. Therefore, in the rest of the analysis, the unconditional nonlinear growth model was used as the base model.

Table 13. Unconditional nonlinear growth model - sophomores

Unconditional Nonlinear Growth Models - Sophomore Year

Predictors	**RED**	**CON**	**EPS**	**CAL**	**CUS**	**RE**	**VV**
	Est. (std.err)	**Est. (std.err)**	**Est. (std.err)**	**Est. (std.err)**	**Est. (std.err)**	**Est. (std.err)**	**Est. (std.err)**
Intercept	3.85 (0.10)***	3.53 (0.10)***	3.56 (0.11)***	3.48 (0.14)***	2.74 (0.11)***	2.56 (0.24)***	0.94 (0.12)***
Months	0.30 (0.03)***	0.27 (0.03)***	0.22 (0.03)***	0.29 (0.04)***	0.23 (0.03)***	0.24 (0.03)***	0.20 (0.04)***
Months^2	-0.07 (0.01)***	-0.07(0.01)***	-0.02 (0.01)***	-0.06 (0.01)***	-0.02 (0.01)*	-0.02 (0.01)*	-0.04 (0.01)***
Fit Statistics							
-2 Log Likelihood	506.3	538.2	561.5	641.5	543.4	540.6	604.9
Incremental Chi-Square	36.8	30.2	2.0	18.1	3.4	2.5	9.6
Degree of Freedom	1	1	1	1	1	1	1
P-Value	p<0.001	p<0.001	p<0.001	p<0.001	p<0.001	p<0.001	p<0.001

***denotes p<0.01; **denotes p<.05; *denotes p < 0.10. Sample size, n=39.

4.5.1.2 Conditional Nonlinear Growth Model with Self-efficacy

Using the unconditional nonlinear growth model, student-level predictors were added (i.e., the self-efficacy factors) to investigate whether the intercepts and linear and nonlinear slopes of modeling performance growth vary as a function of self-efficacy. A specific non-linear growth model was specified for each modeling outcome, where the outcome was the dependent variable and associated theoretical self-efficacy factors were the independent variables.

Similar to the unconditional models, only the linear and quadratic terms of the time variable (i.e., months and squared months) were included in the level 1 equations. In the level 2 equations, we included all the related self-efficacy factors as the student-level predictor. We tested models using various combinations of the independent variables and control variables, and report the models that provided the most meaningful interpretations in Figure 13. Accordingly, γ_{00k} represents the average intercepts in of the growth model, γ_{10k} represents the average slopes of the linear term (where *k=1,2,…7* stands respectively for the modeling outcomes RED, CON, EPS, CAL, CUS, RE and VV). To ensure that the fixed effects can be interpreted properly, self-efficacy scores were centered at mean zero, as well as the time variable.

The Conditional Nonlinear Growth Models Tested for Self-Efficacy

Modeling Outcome	Model/ Level 1	Model / Level 2
RED	$Y_{ij\,RED} = \beta_{0\,jRED} + \beta_{1\,jRED} Month + \beta_{2\,jRED} Month^2 + e_{ijRED}$,	$\beta_{0\,j\,RED} = \gamma_{00} + \gamma_{01} SE_{RED} + \delta_{0\,j\,RED}$, $\beta_{1\,j\,RED} = \gamma_{10} + \gamma_{11} SE_{RED} + \delta_{1\,j\,RED}$
CON	$Y_{ijCON} = \beta_{0\,jCON} + \beta_{1CON} Month + \beta_{2\,jCON} Month^2 + e_{ijCON}$	$\beta_{0\,j\,CON} = \gamma_{00} + \gamma_{01} SE_{CON} + \gamma_{02} SE_{PM} + \delta_{0\,j\,CON}$, $\beta_{1\,j\,CON} = \gamma_{10} + \gamma_{11} SE_{CON} + \gamma_{12} SE_{PM} + \delta_{1\,j\,CON}$
EPS	$Y_{ijEPS} = \beta_{0\,jEPS} + \beta_{1\,jEPS} Month + \beta_{2\,jEPS} Month^2 + e_{ijEPS}$	$\beta_{0\,j\,EPS} = \gamma_{00} + \gamma_{02} SE_{EPS} + \delta_{0\,j\,EPS}$, $\beta_{1\,j\,EPS} = \gamma_{10} + \gamma_{11} SE_{EPS} + \delta_{1\,j\,EPS}$
CAL	$Y_{ijCAL} = \beta_{0\,jCAL} + \beta_{1\,jCAL} Month + \beta_{2\,jCAL} Month^2 + e_{ijCAL}$,	$\beta_{0\,jCAL} = \gamma_{00} + \gamma_{01} SE_{PM} + \gamma_{02} SE_{IE} + \delta_{0\,jCAL}$, $\beta_{1\,jCAL} = \gamma_{10} + \gamma_{11} SE_{PM} + \gamma_{12} SE_{IE} + \delta_{1\,jCAL}$
CUS	$Y_{ijCUS} = \beta_{0\,jCUS} + \beta_{1\,jCUS} Month + \beta_{2\,jCUS} Month^2 + e_{ijCUS}$,	$\beta_{0\,jCUS} = \gamma_{00} + \gamma_{01} SE_{CAL} + \gamma_{02} SE_{UV} + \delta_{0\,jCUS}$, $\beta_{1\,jCUS} = \gamma_{10} + \gamma_{11} SE_{CAL} + \gamma_{12} SE_{UV} + \delta_{1\,jCUS}$
RE	$Y_{ijRE} = \beta_{0\,jRE} + \beta_{1\,jRE} Month + \beta_{2\,jRE} Month^2 + e_{ijRE}$,	$\beta_{0\,jRE} = \gamma_{00} + \gamma_{01} SE_{IE} + \delta_{0\,jRE}$, $\beta_{1\,jRE} = \gamma_{10} + \gamma_{11} SE_{IE} + \delta_{1RE}$
VV	$Y_{ijVV} = \beta_{0\,jVV} + \beta_{1\,jVV} Month + \beta_{2\,jVV} Month^2 + e_{ijVV}$,	$\beta_{0\,jVV} = \gamma_{00} + \gamma_{01} SE_{IE} + \gamma_{02} SE_{UV} + \delta_{0\,jVV}$, $\beta_{1\,jVV} = \gamma_{10} + \gamma_{11} SE_{IE} + \gamma_{12} SE_{UV} + \delta_{1\,jVV}$

Figure 13. The conditional nonlinear growth models tested for self-efficacy impact

The factor scores (independent variables) were coded (0,1) to indicate low or high self-efficacy category, where the students obtained a one if their self-efficacy was above the mean level for that factor, and zero otherwise. We used a dummy coding since the results were more meaningful than the ones obtained using the continuous values. Results of the unconditional models are given the following sets of tables.

Table 14. Growth models with self-efficacy-part I

Growth Models with Self-efficacy- Sophomore Year- Linear Effect			
Predictors	**RED**	**CON**	**EPS**
	Est. (std.err)	**Est. (std.err)**	**Est. (std.err)**
Intercept	2.97 (0.47)***	2.86 (0.44)***	1.68 (0.46)**
Main Effects			
Months	0.27 (0.03)***	0.23 (0.03)***	0.20(0.03)***
SE_{RED}	-0.19 (0.31)		
SE_{PM}		0.74 (0.5)*	
SE_{CON}		-0.01 (0.25)	
SE_{EPS}			0.50 (0.27)*
Interaction			
SE_{RED} x Months	0.04 (0.11)		
SE_{PM} x Months		-0.20 (0.21)	
SE_{CON} x Months		0.09 (0.11)	
SE_{EPS} x Months			0.05 (0.10)
Control Variables			
Gender (Female)	0.09 (0.16)	0.07 (0.14)	-0.01 (0.15)
MEA (Tire MEA)	-0.75 (0.11)***	-0.71 (0.13)***	-0.11 (0.14)
CGPA	0.27 (0.16)*	0.19 (0.15)	0.61 (0.15)**
Fit Statistics			
-2 Log Likelihood	500.6	537.2	546.4
P-Value	p<0.05	p<0.05	p<0.05

Mark *** denotes p <0.001, ** denotes p <0.05, * denotes p <0.1 and close values. Sample size n=39.

Table 14 (Continued)

Growth models with self-efficacy- Sophomore Year

Predictors	**CAL**	**CUS**	**RE**	**VV**
	Est. (std.err)	**Est. (std.err)**	**Est. (std.err)**	**Est. (std.err)**
Intercept	2.44 (0.65)***	1.36 (0.46)***	1.51 (0.45) **	0.85 (0.58)
Main Effects				
Months	0.24 (0.04)***	0.24 (0.03)***	0.24 (0.03)**	0.19 (0.04)***
SE_{PM}	0.49 (0.77)			
SE_{IE}	-0.19 (0.23)		0.03 (0.19)	-0.28 (0.28)
SE_{CAL}	0.87 (0.53)*	0.56 (0.30) *		0.37 (0.36)
SE_{UV}		0.34 (0.23)		
Interaction				
SE_{PM} x Months	0.04 (0.29)			
SE_{IE} x Months	0.11 (0.11)		0.02 (0.07)	-0.12 (0.10)
SE_{CAL} x Months	-0.13 (0.19)	0.01 (0.11)		0.14 (0.13)
SE_{UV} x Months		0.04(0.10)		
Control Variables				
Gender (Female)	0.44 (0.22)*	- 0.08 (0.16)	0.01 (0.15)	- 0.10 (0.20)
MEA (Tire MEA)	0.07 (0.16)	0.2 (0.12)*	0.28 (0.13)*	0.38 (0.14)**
CGPA	0.26 (0.22)	0.4 (0.16)*	0.35 (0.15)*	0.03 (0.20)
Fit Statistics				
-2 Log Likelihood	631.7	525.6	533.2	603.2
P-Value	p<0.05	p<0.05	p<0.05	p<0.05

Mark *** denotes p <0.001, ** denotes p <0.05 , * denotes p <0.1 and close values. Sample size n=39 with four time points.

Table 15. Growth models with self-efficacy-part II

Growth Models with Self-efficacy- Sophomore Year- Nonlinear

Predictors	**RED** Est. (std.err)	**CON** Est. (std.err)	**EPS** Est. (std.err)
Intercept	2.98 (0.47)***	2.95 (0.44)***	1.73 (0.46)***
Main Effects			
Months	0.27 (0.03)***	0.26 (0.04)***	0.23(0.03)***
Months^2	-0.02 (0.03)	-0.06 (0.03)*	-0.05 (0.03)*
SE_{RED}	-0.02 (0.41)		
SE_{PM}		0.75 (0.41)*	
SE_{CON}		-0.02 (0.37)	
SE_{EPS}			1.09 (0.41)**
Interaction			
SE_{RED} x Months	0.09 (0.12)		
SE_{PM} x Months		-0.15 (0.22)	
SE_{CON} x Months		0.09 (0.12)	
SE_{EPS} x Months			0.15 (0.11)
Trajectory			
SE_{RED} x Months^2	-0.03 (0.04)		
SE_{PM} x Months^2		0.04 (0.10)	
SE_{CON} x Months^2		0.01 (0.04)	
SE_{EPS} x Months^2			-0.09 (0.06)
Control Variables			
Gender (Female)	0.09 (0.16)	0.08 (0.14)	0.01 (0.15)
MEA (Tire MEA)	-0.54 (0.29)*	-0.10 (0.35)	0.47 (0.32)
CGPA	0.27 (0.16)*	0.19 (0.15)	0.61 (0.15)**
.			
Fit Statistics			
-2 Log Likelihood	498.6	533.4	539.2
P-Value	p<0.05	p<0.05	p<0.05

Mark *** denotes p <0.001, ** denotes p <0.05, * denotes p <0.1 and close values. Sample size=39.

Table 15 (Continued)

Growth models with self-efficacy- Sophomore Year

Predictors	**CAL**	**CUS**	**RE**	**VV**
	Est. (std.err)	**Est. (std.err)**	**Est. (std.err)**	**Est. (std.err)**
Intercept	2.49 (0.65)***	1.34 (0.46)***	1.50 (0.45) **	0.90 (0.58)
Main Effects				
Months	0.27 (0.04)***	0.24 (0.03)***	0.25 (0.03)**	0.21 (0.04)***
Months^2	-0.07 (0.04)*	-0.02 (0.03)	-0.02 (0.03)	-0.05 (0.03)
SE_{PM}	0.28 (0.99)			
SE_{IE}	-0.23 (0.37)		0.29 (0.26)	-0.27 (0.35)
SE_{CAL}	1.37 (0.60)**	0.94 (0.40) **		0.64 (0.48)
SE_{UV}		0.45 (0.33) †		
Moderation				
SE_{PM} x Months	-0.06 (0.33)			
SE_{IE} x Months	0.10 (0.12)		0.07 (0.08) †	-0.09 (0.12)
SE_{CAL} x Months	0.07 (0.24)	0.10 (0.13)		0.16 (0.14)
SE_{UV} x Months		0.07(0.10)		
Trajectory				
SE_{PM} x Months^2	0.07 (0.12)			
SE_{IE} x Months^2	0.01 (0.04)	-0.07 (0.05) *	-0.04 (0.03)	0.01 (0.04)
SE_{CAL} x Months^2	-0.11 (0.07)†	-0.02 (0.04)		0.04 (0.05)
SE_{UV} x Months^2				
Control Variables				
Gender (Female)	0.44 (0.22)*	- 0.07 (0.16)	0.02 (0.15)	- 0.09 (0.20)
MEA (Tire MEA)	0.07 (0.41)	0.49 (0.29)	0.49 (0.32)	0.15 (0.35)
CGPA	0.27 (0.22)	0.46 (0.15)**	0.35 (0.15)**	0.03 (0.20)
Fit Statistics				
-2LogLikelihood	625.8	522.4	530.5	599.6
P-value	p< 0.05	p< 0.05	p< 0.05	p< 0.05

Mark *** denotes p <0.001, ** denotes p <0.05 , * denotes p <0.1 and close values. Sample size=39.

An analysis of the tables shows that self-efficacy influences modeling growth through two mechanisms, its main effect and its moderating effect on the linear slope of growth on four out of the seven outcomes that were of interest. Overall, we observe that four of the modeling outcomes had the main effects, and nearly two models showed moderating impact.

The significant main effects of self-efficacy are observed for Conceptual Modeling (CON), Establishing Performance Criteria (EPS), Calculational Modeling (CAL), and Carrying out the Computations and Sensitivity Analysis (CUS). All effects were significant with positive coefficients. The coefficients imply that for these three particular modeling outcomes, one can observe the impact of high self-efficacy starting from the early days of education for the student, and without having to wait for the modeling experience to take place. The commonality between them is the math ability: the ability of the student to understand what is to be calculated, then build and calculate the model correctly. Based on this outcome, one could speculate that the direct effects of self-efficacy on modeling can be linked to the math self-efficacy of the student. Higher self-efficacy levels prove to be an important determinant of the modeling outcome. In particular, when a student is categorized as having high self-efficacy, as opposed to low self-efficacy, his outcome grade on the sheet can be higher than his counterpart with lower self-efficacy.

In addition, self-efficacy was observed to have a higher impact on certain modeling outcomes as more time passes. This moderating impact (or significant interaction with Months) of self-efficacy was observed for Development of a Calculational Model (CON) and Results Evaluation (RE). We also note that significant linear interaction was positive; and nonlinear interaction was negative, suggesting that higher self-efficacy, paired with time (learning and experience effects) can lead to even further gaps in the modeling outcomes in a concave manner.

In other words, at the end of sophomore year the impact of self-efficacy is higher in determining the grade of a student compared to the middle of the semester. It is possible to explain, looking at the sophomore level curriculum, why the differences might be higher for these three modeling outcomes at the end of the sophomore year, when the student has higher self-efficacy.

Conceptual Model Development (CON) can be linked more to the experience with modeling than to learning effects. Here, the more the student is exposed to MEAs, the more likely that there is improvement over time. Paired with higher levels of self-efficacy, we observe that students are better able to reflect their enhanced modeling experience on the modeling outcomes.

Finally, Results Evaluation (RE) is related to the enhanced understanding of numerical results over time. In addition, we observe no effect of self-efficacy on Validation and Verification (VV). This is partially due to the fact that there was minimal change in this outcome. Validation and Verification is typically taught at the upper level (junior and senior) classes at the institution of measurement. Review and Analysis of Data (RED), using statistical techniques, is taught and well practiced all through the sophomore year. At the end of the sophomore level, the students learn descriptive statistics, distributions, sampling, outliers, plotting data and other commonly used engineering data analysis methods, many of which are first introduced during the freshman year. The small change in knowledge even when paired to higher levels of self-efficacy is not observable in the modeling outcomes at the end of the two semesters. The fact that self-efficacy can lead to a difference in the modeling outcomes is a significant finding since it suggests that pairing high self-efficacy with education can further achievements in modeling outcomes . The educational practice take-away from this observation is that, it is not enough to have high self-efficacy to observe superior modeling outcomes.

However, it is also clear that without high levels of self-efficacy, educational premises are not reaching their full potential. This study, therefore, can be seen as a call for engineering educators to develop and implement practices that are geared towards increasing self-efficacy while providing modeling experiences.

Next we tested whether having higher self-efficacy increases the trajectory of growth. If observed to be significant, self-efficacy would prove to accelerate or decelerate the time to reach an outcome score, beyond the linear effect. However, our statistical tests showed that the nonlinear time moderation effects were not significant.

We tested the impact of gender, specific MEA and GPA. In four of the models GPA had a significant and positive influence on the development (i.e., RED, EPS, CUS and RE). Why would a student with higher cumulative GPA over time achieve higher scores on setting the goal, and interpreting the results? The explanation for this finding is rather intuitive. If a student is inherently better at identifying what is being asked of her and reporting the results correctly, these are likely to have an impact on her traditional course grades. In the non-linear models, gender was significant only in CAL and MEA only in RED, thus no consistent pattern of Gender and MEA existed over all the outcomes. Additional models that included the interactions of gender and self-efficacy levels were tested, but no consistent, significant patterns were observed. Since these variables are not the focus of this research, these analyses are not further described.

4.5.2 Analysis of Sophomore and Senior Student Differences

A secondary set of models were developed to understand the predictive power of self-efficacy given differences in student level , as well as GPA, gender and the type of MEA. In doing so, we ask the question, assuming that students grow in their modeling skills from the sophomore to senior year, how does the self-efficacy level effect the changes in modeling? To answer this question, with self-efficacy factor scores as independent variables, the difference in modeling outcomes was tested. In the testing, only cohorts II and III were included. Both the data from Tire and CNC Machine MEAs were included in the tests, where a dummy MEA variable differentiated which MEA the outcome scores were coming from.

Similar to the growth models, these regression models tested for differences between sophomores and seniors accounting for whether or not the student held high self-efficacy beliefs. Yet the independent variables, unlike the growth models, were not dummy coded, and continuous self-efficacy scores were used (i.e., scores were mean centered around zero). The cohort variable was dummy coded, and it equaled one if the student belonged to senior year and zero otherwise. Gender and MEA were dummy coded (1 = female, 1= Tire Reliability MEA, and zero otherwise). Cumulative GPA (CGPA), which controls for the overall success of the student, was continuous; and was measured from the semester prior to the MEAs. The results of the regression models are given in Table 16 and Table 17.

Table 16. Sophomore to senior year change in modeling with self-efficacy- Part I

Sophomore to senior year changes- Part I

Predictors	**RED** **Est. (std.err)**	**CON** **Est. (std.err)**	**EPS** **Est. (std.err)**
Intercept	3.17 (0.61)***	3.50 (0.68)***	3.63 (0.54)***
Cohort (Seniors)	0.26 (0.2)	0.65 (0.21)**	1.26 (0.17)***
SE_{RED}	0.41(0.21)*		
SE_{RED} x Cohort (Seniors)	0.94(0.48)*		
SE_{PM}		0.13 (0.21)	
SE_{PM} x Cohort (Seniors)		-0.46 (0.41)	
SE_{CON}		-0.07 (0.18)	
SE_{CON} x Cohort (Seniors)		0.64 (0.35)*	
SE_{EPS}			0.25(0.16)
SE_{EPS} x Cohort (Seniors)			0.20(0.24)
Gender (Female)	0.15 (0.20)	-0.03 (0.22)	0.18 (0.18)
CGPA	0.27 (0.21)	0.14 (0.23)	0.17 (0.18)
MEA (Tire)	-0.14 (0.17)	-0.36(0.19)*	-0.22 (0.15)
Fit Statistics			
R^2	0.16	0.12	0.37
F-value	4.99	2.56	14.96
Degrees of Freedom	6	6	6
P-Value for model	p<0.01	p<0.01	p<0.001

***denotes p<0.01; **denotes p<.05; *denotes p < 0.10.

Table 17. Sophomore to senior year change in with self-efficacy- part II

Sophomore to senior year changes with self-efficacy- Part II

Predictors	**CAL**	**CUS**	**RE**	**VV**
	Est. (std.err)	**Est. (std.err)**	**Est. (std.err)**	**Est. (std.err)**
Intercept	2.83 (0.86)**	2.92 (0.53) ***	1.74 (0.77)**	2.25 (0.84)**
Cohort (Seniors)	-0.10 (0.30)	0.52 (0.18)**	0.89 (0.25)**	0.82 (0.26)**
SE_{PM}	0.29 (0.29)			
SE_{PM} x Cohort (Seniors)	-0.86 (0.55)			
SE_{IE}	-0.10 (0.23)	0.89 (0.38)**	0.34 (0.19)*	
SE_{IE} x Cohort (Seniors)	0.90 (0.55)	0.75 (1.13)	- 0.64 (0.40)	
SE_{CAL}	1.34 (0.62)**	0.14 (0.13)		
SE_{CAL} x Cohort (Seniors)	-0.74 (1.83)	-0.15 (0.27)		
SE_{UV}				-0.30 (0.24)
SE_{UV} x Cohort (Seniors)				0.24 (0.27)
Gender (Female)	0.44(0.27)	-0.22(0.17)	0.17 (0.26)	0.04 (0.26)
CGPA	0.39(0.29)	0.23 (0.18)	0.51 (0.26)	-0.22 (0.28)
MEA (Tire)	-0.70 (0.23)**	0.08 (0.15)	0.25 (0.22)	-0.61(0.23)**
Fit Statistics				
R^2	0.14	0.19	0.18	0.14
F-value	1.97	3.22	5.32	3.10
Degrees of Freedom	9	9	9	9
P-Value	p<0.05	p<0.001	p<0.001	p<0.001

***denotes p<0.01; **denotes p<.05; *denotes p < 0.10.

As shown in the tables, models were all significant as measured by the F-value, but the R^2 values were low (0.12-0.37). Given that almost all the independent variables were categorical in the regression, the low R^2 values were rather expected. R^2 levels are higher (0.37) in the model for EPS, where the change is independent of any variables other than the cohort. Yet, based on the low R^2 levels, the findings will be treated as exploratory rather than explanatory.

We find that the intercepts and cohort variable (being a senior student) are significant (and positive) in five out of the seven models. This implies that even without accounting for the impact of self-efficacy, there is a growth in modeling skills after the sophomore year is over, as well. We notice that that there is a not significant change in Review and Evaluation of Data (RED), and Development of Calculational Models (CAL). The finding that RED does not change much is complementary to the results from the sophomores. From the growth models, it was found that by the end of the sophomore year, the students are reaching a high level in RED. It is likely that majority of the learning related to data analysis takes place in the sophomore year. Similarly, development of calculational models not showing a significant development is relatively puzzling. This finding might be a function of the MEAs requiring statistical knowledge, which is commonly taught at the sophomore year.

The highest jump in outcomes between the sophomore and seniors (before self-efficacy effects are accounted for) is observed in Establishing the Performance Criteria (EPS), which the cohort coefficient 1.26. This implies that by the time a student reaches senior year, he is much more accurate in identifying the expected goal of the exercise. This includes accurately identifying what is asked of the student and what is to be calculated within the model.

Between the sophomore and senior years, the students develop significantly in regards to identification of goals and criteria to be calculated out of the created models. The most likely reason for the high development in EPS is the increasing exposure to modeling exercises.

Complementary to the findings of the growth models, self-efficacy has a significant main effect on four models, including Review and Evaluation of Data (RED), Development of a Calculational Model (CAL), Carrying out Calculational Models (CUS), and Results Evaluation (RE). This implies that comparing the changes between sophomore to senior year, the main effect of higher self-efficacy on CAL and CUS are still observable. Once again, these factors of self-efficacy are significantly related to math self-efficacy, and one could speculate that the inherent differences in math self-efficacy remain to influence the students' ability to model over the years. Differently from the sophomore year, we observe now the main effects of Review and Evaluation of Data (RED) and Results Evaluation (RE) are significantly influenced by the level of self-efficacy. It is possible that after the sophomore year, the self-efficacy levels better reflect the abilities in these two categories. Similarly, the moderating influence of self-efficacy on time was observed positively and significantly for the modeling outcomes RED and CON. Self-efficacy further enhances the modeling outcome achieved.

The only two outcomes where no significant influences were observed were EPS and VV. The results once again suggest and validate the outcomes obtained at the sophomore level with respect to the influence of self-efficacy. In addition, no significant gender or CGPA effects were observed. The only influence of the control variables were the MEA type, where Tire Reliability MEA resulted in lower outcomes for CON, CAL, and VV outcomes of the model for the average student. It was observed that the students struggled more with the Tire MEA; as such, cohort and self-efficacy had higher coefficients than the coefficient of Tire MEA, except for Validation and Verification. However, this outcome overall was not observed for all the students. The most likely reason for it is the fact that students learn about validation and verification much later in their undergraduate education and therefore they are not able to reflect it on their work fully.

4.6 SUMMARY OF STUDY 1

In this study we developed a self-efficacy instrument directed at engineering modeling. Modeling is a critical and fundamental aspect of being an engineer; and in an already crowded curriculum, teaching modeling is becoming an increasingly bigger challenge. Self-efficacy has been widely studied in other academic fields. Yet, in engineering education, there are few studies that attempt to understand how self-efficacy effects the motivation of the engineering student.

EMSS instrument provided a potentially reliable scale of the modeling stages that matches the theoretical stages. In addition, the conducted studies help to validate the scale and provide confirmatory results. The scale was tested on data collected from industrial and civil engineering students at both the sophomore and senior levels.

Our empirical results suggest that the factors of self-efficacy can be discriminated from one another empirically, we support the use of substitute methods of data collection in future studies. For example, assessments of student self-efficacy and modeling performance could be obtained from teachers and peers, or from more objective sources. With the exception of Validation and Verification, we were able to show that the self-efficacy did influence the expected outcome. Therefore, we contribute to the external validity of self-efficacy theory by showing its applicability in a new research domain.

Despite the overall positive trend in one of the two disciplines, there were only a few dimensions in which significant improvement was observed. Further, students themselves were not rating themselves excellent in any of these dimensions, such as carrying out calculational models. Industrial engineering students had an improvement over the civil engineers by the time both had reached their senior year, and overall, there was a tendency for lower variation in self-efficacy scores when students reached their senior year. It is plausible to suggest that additional real life experiences are required at the undergraduate level to change this observation, since more modeling experiences can help to establish higher self-efficacy. Educational interventions such as MEAs, problem based learning, etc., may contribute to development of self-efficacy beliefs by providing better modeling experience compared to text-book problems.

Results of the study suggest that differences between sophomores and seniors imply that improvement in student self-efficacy in engineering modeling can be realized; and in particular significance was observed in the industrial engineering group for three dimensions (i.e., Process Modeling, Interpretation, and Uncertainty and Validation). For the most part, these three dimensions are relatively abstract, and it is expected that such concepts and how students cope with them as they build their skills in modeling evolves as they matriculate to seniors. In addition, there is a tendency for the female students and sophomore level students to report lower levels of self-efficacy.

In the rest of the study, we demonstrate that for certain modeling exercises, self-efficacy can also precede the level of development in modeling ability growth. In the growth models, the significant main effects of self-efficacy are observed for Conceptual Model Development (CON), Establishing a Performance Criteria (EPS), Calculational Modeling (CAL), and Carrying out the Computations and Sensitivity Analysis (CUS). All effects were significant with positive coefficients, implying that one can observe the impact of high self-efficacy starting from the early days of education for the student, and without having to wait for the modeling experience to take place. Based on this outcome, modeling self-efficacy can be linked to the math self-efficacy of the student. Higher self-efficacy levels prove to be an important determinant of the modeling outcome. In addition, self-efficacy was observed to have a moderating impact for Development of a Conceptual Model (CON) and Results Evaluation (RE). Linear interaction was positive; suggesting that higher self-efficacy, paired with time (learning and experience effects) can lead to even further gaps in the modeling outcomes. In other words, at the end of sophomore year the impact of self-efficacy is higher in determining the grade of a student compared to the middle of the semester.

In comparing the sophomores to seniors, self-efficacy had a significant main effect on four models, including Review and Evaluation of Data (RED), Development of a Calculational Model (CAL), Carrying out Calculational Models (CUS), and Results Evaluation (RE). Again, the factors of self-efficacy were significantly related to math self-efficacy. Differently from the sophomore year, main effects of Review and Evaluation of Data (RED) and Results Evaluation (RE) were significantly influenced by the level of self-efficacy. The moderating influence of self-efficacy on time was observed positively and significantly for the modeling outcomes RED and CON. Self-efficacy further enhances the modeling outcome achieved. The only two outcomes where no significant influences were observed were the EPS and VV outcomes. In addition, no significant gender or CGPA effects were observed. The only influence of the control variables were the MEA type, where Tire Reliability MEA resulted in lower outcomes for CON, CAL, and VV outcomes of the model for the average student. It is observed that the students had more difficulty with the Tire MEA; and as such cohort and self-efficacy had higher coefficients than the coefficient of Tire MEA, except for the Validation and Verification model. The implications of these results, along with suggestions for the educators are discussed in detail in the overall summary, section 8.1.

5.0 STUDY 2: IMPACT OF EPISTEMOLOGY ON GROWTH OF MODELING

5.1 MOTIVATION

The emphasis on modeling in engineering schools is increasing. For instance, the engineering systems division (EDS) at MIT has adopted an official vision statement to become the leader in modeling complex systems. Following this, the faculty at MIT reflected on epistemology and its relationship to engineering systems as a first step (Frey 2003). In agreement with recent calls to action, the relationship between epistemology and engineering modeling is the focus of this study.

Epistemology is concerned with the nature of knowledge, justification, evidence, and related notions. By epistemic cognition, we refer to the processes in which individuals engage in order to consider the criteria, limits, and certainty of knowing (Kitchener 1983). Epistemic beliefs have been shown to correlate with learning on multiple dimensions (Duell and Schommer-Aikins 2001, Bendixen and Hartley 2003), including metacognition (Hofer 2004; Bendixen and Hartley 2003), self-regulation (Muis 2007), comprehension (Hartley and Bendixen 2001), scientific argumentation and reasoning (Duschl and Osborne 2002, Sandoval 2003, Sandoval and Reiser 2004) and the ability to solve a problem (Schommer-Aikins, Duell, and Hutter 2005).

In this study, we extend prior findings and investigate whether an engineering student's epistemic beliefs can influence his modeling skills. Although previous research suggests that motivational processes are related to academic achievement (Ames and Archer 1988, Dweck 1986), to date, we have not observed that the ability to abstract and represent real world aspects through a model has been the subject of rigorous inquiry.

Based on prior literature on epistemology, we investigate three objectives. First, we aim to understand how students' epistemic cognition influences the growth of their modeling skills over the course of one academic year. Second, we aim to investigate differences between modeling skills of engineering students at sophomore and senior years, and how their epistemic beliefs impact these differences. We conduct this modeling skills assessment through the use of Model-eliciting activities (MEAs), which are special engineering modeling exercises. Our final objective is to discuss the potential epistemic characteristics of MEAs; and how students' epistemic beliefs may contribute to the understanding of how students can be educated to become better modelers.

Our findings suggest that development of modeling skills are affected by personal epistemology. Overall, the more sophisticated a student's beliefs are, the higher the level of modeling ability is attained, having controlled for effects of conceptual learning, gender and GPA. This suggests that development of modeling ability may be constrained if one's personal epistemology is naïve.

5.2 BACKGROUND

5.2.1 Epistemic Beliefs and Modeling

Epistemic beliefs characterize the way in which individuals view the world (the external, physical reality, themselves, or ideas) to gain knowledge (Maggioni and Parkinson 2008). The literature in the area of epistemology started with Perry's (1970) study of undergraduate epistemological beliefs and regained momentum with Schommer (1990). Whereas Perry and earlier works assumed that epistemic beliefs were unidimensional, beginning with Schommer (1990) personal epistemology was depicted with multiple dimensions.

Schommer's description (1990) of personal epistemology involved independent beliefs conceptualized about the simplicity, certainty, and source of knowledge, as well as beliefs about the control and speed of knowledge acquisition. The hypothesized five dimensions of epistemology were as follows:

1. *Simple Knowledge:* ranges from the belief that knowledge is best characterized as isolated bits and pieces to the belief that knowledge is best characterized as highly interrelated concepts;

2. *Certain Knowledge*: ranges from the belief that knowledge is absolute and unchanging to the belief that knowledge is tentative and evolving;

3. *Innate Ability*: ranges from the belief that ability to learn is given at birth to the view that ability to learn can be increased);

4. *Quick Learning*: ranges from the belief that learning takes place quickly or not at all to the belief that learning is gradual; and

5. *Source of Knowledge* (*Omniscient Authority*): ranges from the belief that knowledge is handed down by authority to the belief that knowledge is derived from reason.

Schommer- Aikins suggested a 63-item questionnaire, often referred to as Epistemic Beliefs Questionnaire (EBQ), with multiple items written to assess each of the five proposed dimensions. Despite the theoretical dimensions, reported factor analyses yielded only the first four factors (Schommer, Crouse, and Rhodes 1992, Schommer 1990). The dimension "source of knowledge" (omniscient authority) was not a significant factor. Although commonly used, EBQ has been criticized, because the factor analysis utilized only 12 subsets of the 63 items as variables rather than the individual items, suggesting an erroneous methodology potentially impacting the observed factor solutions (Hall, Snell, and Foust 1999). This failure resulted in follow up studies to test for similar factor structures. For example Qian and Alverman (1995) extracted factors of EBQ after eliminating the items related to source of knowledge, yet, only simple knowledge, certain knowledge, fixed ability, and quick learning survived. Furthermore, the dimensions of simple and certain knowledge were combined into a single factor. In another study, Hofer (2000) analyzed the factor structure of 32 items of EBQ and obtained all four factors individually.

Schraw, Bendixen, and Dunkle (2002) failed to extract these four factors using all of the 63 items. Later, they reduced EBQ into 32 items, and called it the Epistemic Beliefs Inventory (EBI). Unlike EBQ, EBI reported five clean factors (also noted above) as (1) quick learning (learning occurs in a quick or not-at-all fashion), (2) simple knowledge (knowledge consists of discrete facts), (3) certain knowledge (knowledge is certain and not flexible), (4) innate ability (the ability to acquire knowledge is innate), (5) omniscient authority (authorities have access to otherwise inaccessible knowledge). The internal consistency coefficients for these factors ranged from 0.67 to 0.87. As a result, in this study, we preferred to use the EBI.

Epistemological beliefs may differ for students in *hard* (e.g., mathematics and science) or *soft* (e.g., social science and humanities) domains. Some studies report that students hold more naive epistemological beliefs in hard domains; for instance, engineering students were reported to be more likely to believe in the certainty of knowledge than students in social science and humanities (Jehng, Johnson, and Anderson 1993), and medical students expressed more dualistic views of knowledge (knowledge is right or wrong, true or false) than psychology students (Lonka and Lindblom-Ylanne 1996). Hofer (2000) suggested that students regarded knowledge more certain, less justified by personal knowledge and first-hand experience in science than in psychology.

The term naïve epistemic beliefs should not give the impression that some students are better or worse than others. Rather, naiveté is related to the nature of the domain, for example, how structured it is (Hofer 2000, Buehl and Alexander 2001, Hofer and Pintrich 1997) or the traditional educational practices in a particular domain. In addition, based on the task, such naiveté can be helpful or hurtful. Buehl and Alexander (2001) concluded differences in epistemological beliefs are related to differences in the nature of domains, differences in the way domains are taught, or differences in the nature of domains and instruction combined. In particular, if the task is ill-structured (i.e., when information is complex and probabilistic, and the required tasks cannot be definitely predetermined), students holding less sophisticated and less flexible epistemic beliefs recall, learn, argue, and solve problems worse than students who hold sophisticated and flexible epistemic beliefs (Stathopoulou and Vosniadou 2007, Mason and Scirica 2006). On the other hand, when tasks are well-structured, holding sophisticated epistemological beliefs can interfere with recall and comprehension (Braten, Stromso and Olaussen 2008). Further, epistemic beliefs depend on age, education, and political affiliations of college students (Unger, Draper, and Pendergrass 1986). It is therefore possible for each student even within the same domain (here, engineering) to hold different epistemologies formed before starting their formal engineering education; and these initial beliefs can potentially intervene with the ability to learn and develop modeling skills.

5.2.2 MEAs and Epistemology

In this section, we state the case for linking MEAs to an epistemic pedagogy. Model Eliciting Activities (MEAs) are activities that are designed to help students link their prior knowledge while constructing new knowledge as they engage in solving the posed problem; thereby learning to identify engineering content, as well as implementing modeling skills. They are built around different engineering content knowledge and topics, which are explored adhering as much as possible to constructivist principles. Students are given opportunities to think, control and manage their thinking as they solve problems and perform modeling tasks, activating their metacognitive abilities while working on an MEA. Activities are designed for students to construct their knowledge either from given empirical evidence or let them link their prior knowledge to develop a better understanding of different engineering concepts.

MEA implementation calls for teams that provide the student with an environment to work with other students interested in achieving diverse learning goals. Students engage in these activities on their own and within their team, linking their prior knowledge to reinforce what they already know. By working in teams, students not only become more aware of their actual behaviors in their group, but also potentially influence others. Within a group environment, students may feel more comfortable in acknowledging their lack of knowledge to approach the problem at hand.

MEAs may be helpful in evoking and constructing complex epistemology at an early stage and are valuable in helping students learn how to process new knowledge, particularly when the student does not already possess the full conceptual background. The "real life" stories used to form the basis of the MEAs can help to reinforce the value of engineering practice and make it more accessible to students. The students, having been asked to write down their process instead of a single numerical answer, might also be prompted to ask themselves questions to induce better reflection. The multiple avenues to model a particular MEA can suggest to students that consensus on certain engineering problems is difficult; and thus teach them ways to achieve resolution.

The questions posed in the MEAs require reasoning, thus helping students to correct wrong assumptions, as opposed to textbook problems and examples which have a defined single answer and a presumed solution path. The open ended challenging questions potentially provide the students the opportunity to discuss and offer their solutions with team members, and acknowledge that their ideas can be mutually enriching. All these activities feed back into the epistemic belief systems.

5.3 THEORY

5.3.1 Impact of Epistemic Beliefs on Modeling Growth

A series of articles investigating the impact of epistemic beliefs on learning has provided the underlying theory for this study. In line with the purpose of examining the relationship between epistemic beliefs and engineering modeling skills, we focus on two questions that have not been addressed in preceding studies.

The first is whether or not epistemic beliefs are related to the development of engineering modeling skills, when effects of other critical variables such as age, education, gender, and knowledge are controlled. We hypothesized that epistemic beliefs, apart from other social and personal variables (King and Kitchener 1994, Kohlberg 1984, Kuhn 1991, Piaget 1965), can significantly influence the development of such abilities. The second question is concerned with the specific dimensions of epistemic beliefs and how each dimension relates to stages of modeling. We subsequently construct our theory related to these dimensions.

5.3.1.1 Quick Learning

Findings (based on reading a text) in the epistemic literature suggest that students who believe learning must occur quickly or not at all tend to oversimplify information and perform poorly (Buehl et al. 2001). They tend to make conclusions too quickly, neither providing themselves with sufficient time nor making several iterations to understand the material. Such students tended to draw oversimplified conclusions from the text (after controlling for verbal ability, prior knowledge, and gender), and did poorly on a comprehension test (Buehl et al. 2001). Gifted students were found to believe that intelligence is fixed and that learning occurs quickly or not at all, in accordance with their intellectual gift.

Oversimplification or exclusion of information may be closely linked to evaluation of data. If the student is quick in reading the text, it is likely that some of the important information will be left out, or some of the redundant information is mistaken as important and included in their model. Therefore, we surmise that there may be two modeling stages likely to be less developed when a student believes in quick learning: Review and Evaluation of Data (RED), and Construction of the Model (CAL). Based on the information that is analyzed, or data that is included in the model, a student may carry out the calculational model she developed in the correct form, and develop the right results; but, overall, the input to the modeling process will be influenced by the level of quick learning. Therefore, we posit the following hypotheses.

***H_{1a}*:** *Students believing learning occurs quickly or not at all will develop lower modeling skills to review and evaluate data (RED) compared to students who do not.*

***H_{1b}*:** *Students believing learning occurs quickly or not at all will develop lower modeling skills to construct a mathematical model of the system (CAL) compared to students who do not.*

5.3.1.2 Certain Knowledge

Similar to quick learning, students who believe knowledge is certain tend to draw more absolute and definitive conclusions than students who regard knowledge as more tentative (Buehl et al. 2001). On the contrary, when students believe in uncertainty of knowledge, they are more likely to derive expressions that are inconclusive on a controversial topic (Kardash and Scholes 1996). Students who view knowledge as certain are more likely to misinterpret conclusions from their results and they tend to limit further methods to analyze the data and calculate performance criteria. A proper model should acknowledge the uncertain nature of the real world; and therefore, it is preferred that a student would tend to believe in the uncertainty of knowledge to convey it in a constructed model In addition, too much uncertainty can be expected to have a reverse effect on the engineers.

Certainty of knowledge, therefore, is likely to influence the modeling stages, where the student is expected to conduct analyses based on information received or obtained, such as the stage of Review and Evaluation of data (RED), as well as the uncertainty analysis stage of Calculational Modeling (CUS). If the student believes that the data received do not hold uncertainty, certain engineering concepts (e.g., random variable, variation, or statistical distribution) may be difficult to comprehend during the data evaluation stage. Similarly, when a student believes that the output of a model is certain, it is less likely that he will follow up with sensitivity analysis. We put forward the following hypotheses regarding certain knowledge.

> ***H_{2a}:*** *Students believing knowledge is certain will develop lower modeling skills relative to constructing a mathematical model of the system (CAL) compared to students who do not.*

> ***H_{2b}:*** *Students believing knowledge is certain will develop lower modeling skills to carry out calculations and consider the uncertainty of a model of the system (CUS) compared to students who do not.*

5.4 ANALYSIS

5.4.1 Analysis of Epistemological Impact: Sophomore Year Change

Similar to the analysis of self-efficacy, to analyze changes that took during the sophomore academic year, we used a growth curve model. Again, all models were estimated with full maximum likelihood using PROC MIXED in the SAS statistical package, Version 9.2 (Littell, Milliken, Stroup and Wolfinger, 1996). Our analyses focused on the influence of between-subject factors (i.e., simple knowledge, omniscient authority, fixed ability, certain knowledge and quick learning) on linear and quadratic time as within-subject changes in growth of modeling skills. An unstructured error covariance matrix was specified for each of the models (Long and Pellegrini, 2003). The two unconditional multilevel models (means model, linear and nonlinear growth models) were given in section 4.5.1.1. The results repeat for measuring the impact of epistemic beliefs, and were again used to build the foundation for subsequent analyses.

5.4.1.1 Conditional Nonlinear Growth Model

After selecting the unconditional nonlinear growth model with random effects, we added student-level predictors, i.e., epistemic dimensions (specifically, simple knowledge – SK, omniscient authority – OA, certain knowledge – CK, innate ability – IA, and quick learning – QL) to further investigate whether the intercepts and linear and nonlinear slopes of modeling performance growth vary as a function of these variables. Results from these models can then be used to test the hypotheses. The growth models are as follows.

Level 1: $Y_{ijk} = \beta_{0jk} + \beta_{1jk} Month + \beta_{2jk} Month^2 + e_{ijk}$,

where k=1,….7 for each modeling stage.

Level 2:

$$\beta_{0jk} = \gamma_{00k} + \gamma_{01k} SK + \gamma_{02k} CK + \gamma_{03k} OA + \gamma_{04k} IA + \gamma_{05k} QL + \delta_{0jk},$$

$$\beta_{1jk} = \gamma_{10k} + \gamma_{11k} SK + \gamma_{12k} CK + \gamma_{13k} OA + \gamma_{14k} IA + \gamma_{15k} QL + \delta_{1jk}.$$

As in the unconditional models, only the linear and quadratic terms of the time variable (i.e., months and squared months) were included in the level 1 equations. However, in the level 2 equations, we included all the epistemic dimensions as the student-level predictor. To ensure that the fixed effects can be interpreted properly, we centered the student level predictors at mean zero (Singer 1998). Thus, in this model, γ_{00k} represents the average intercept in the individual growth model, whereas γ_{10k} represents the average slopes of the linear term. The proposed hypotheses were tested by examining the coefficients in the level 2 equations corresponding to the student-level variables. For example, the signs and significance of γ_{01k} and γ_{11k} reflect the impact of student's epistemic belief on the modeling level and growth trajectory of the modeling skills, respectively. The results are reported in Table 18.

The table demonstrates that the intercepts of all models are significant, as well as the months and months squared. In addition the level of epistemic beliefs that the students have shows itself on the growth level and at some instances, also the growth trajectory. The intercept of each model demonstrates the average score of a student after four months, when the impact of epistemic dimensions is taken into account.

Table 18. Growth models with epistemic beliefs- sophomores

Longitudinal Growth in Modeling with Epistemic Beliefs- Sophomore Year

Predictors	**RED**	**CON**	**EPS**	**CAL**	**CUS**	**RE**	**VV**
	Est. (std.err)	**Est. (std.err)**	**Est. (std.err)**	**Est. (std.err)**	**Est. (std.err)**	**Est. (std.err)**	**Est. (std.err)**
Intercept	3.85(0.14)***	3.73(0.15)***	3.52(0.16)***	3.48(0.21)***	2.75(0.17)***	2.60(0.16)***	0.93(0.20)***
Months	0.24(0.05)***	0.26(0.06)***	0.18(0.06)***	0.24(0.07)***	0.22(0.06)***	0.16(0.05)**	0.21(0.07)**
Months^2	-0.07 (0.01)***	-0.07(0.01)***	-0.02(0.01)	-0.06(0.01)***	0.02(0.01)*	0.02(0.01)*	-0.04(0.01)**
Innate Ability	-0.48 (0.15)***	-0.36(0.15)**	-0.28(0.17)*	-0.48(0.23)**	-0.08(0.18)	-0.30(0.16)*	-0.05(0.21)
Quick Learning	-0.38(0.16)**	-0.03(0.16)	-0.09(0.17)	-0.37(0.23)*	0.13(0.19)	-0.08(0.17)	0.29(0.22)
Omniscient Authority	0.18(0.13)	-0.04(0.13)	0.12(0.15)	0.24(0.2)	0.12(0.16)	0.13(0.14)	-0.07(0.19)
Simple Knowledge	-0.25(0.14)*	-0.02(0.14)	-0.39(0.15)**	-0.36(0.20)*	0.02(0.17)	-0.02(0.15)	-0.23(0.19)
Certain Knowledge	0.36(0.16)*	-0.02(0.16)	-0.03(0.18)	0.16(0.24)	-0.16(0.19)	0.12(0.18)	-0.28(0.23)
Innate Ability x Months	0.10(0.06)	0.12(0.07)*	0.04(0.06)	0.11(0.08)	0.02(0.07)	-0.05(0.06)	0.01(0.08)
Quick Learning x Months	0.07(0.06)	0.02(0.07)	0.01(0.07)	0.03(0.09)	-0.03(0.07)	0.03(0.06)	0.08(0.08)
Omniscient Authority x Months	0.08(0.05)	0.05(0.06)	0.11(0.06)*	0.08(0.07)	0.08(0.06)	0.12(0.05)*	-0.01(0.07)
Simple Knowledge x Months	-0.07(0.05)	-0.10(0.06)	-0.05(0.06)	-0.08(0.07)	-0.01(0.06)	0.03(0.05)	-0.02(0.07)
Certain Knowledge x Months	-0.05(0.06)	-0.08(0.07)	-0.02(0.07)	-0.02(0.09)	-0.05(0.07)	0.05(0.06)	-0.08(0.08)
Fit Statistics							
-2 Log Likelihood	480.9	525.8	547.7	627.7	528.0	527.3	599.3
P-Value	p<0.001	p<0.001	p<0.001	p<0.001	p<0.001	p<0.001	p<0.001

***denotes p<0.01; **denotes p<.05; *denotes p < 0.10. Sample size is 39, with four time points included in the measurement.

As expected in hypotheses H_{1a} and H_{1b}, it was suggested that the quick learning (QL) dimension should influence the modeling stages that relate to in depth evaluation of data and information. In two of the models, review and evaluation of data (RED) and constructing a mathematical model (CAL), the particular modeling processes are significantly and negatively influenced by the student's beliefs in 'quick learning'. Specifically, when a student believes that learning should occur quickly, the student is less likely to spend time on the tasks, resulting in lower improvement over these stages.

It was posited that certain knowledge (CK) would influence the modeling processes that relate to dealing with uncertainty in information (CUS) and mathematical modeling (CAL). The information or the data given to student can include multiple unknowns, and some randomness, but if the student believes that there is no flexibility in the truth of information, he is less likely to evaluate data recognizing the randomness, test the results of a mathematical model for sensitivity, and possibly test for validation and verification. Results fail to support hypotheses H_{2a} and H_{2b}. However, we find a significant effect on review and evaluation of data (RED). It is likely that the uncertainty in the model stems from data, and when students are not educated about sensitivity analysis, uncertainty is likely handled though data analysis.

Simplicity of knowledge (SK), a dimension that measures to what extent a student prefers factual information to theory, was claimed to be important in modeling stages that are rather involved where simple facts vs. complex theories can be implemented. This type of complexity can play a role in understanding the data that is provided (RED), setting the goals for a system (EPS), and working on the mathematical calculations of the problem (CAL, CUS), as posited in H_{3a}- H_{3d}. The models indicate support for the hypotheses for the first three models, but not the last model (CUS). One possible explanation for lack of a relationship between simple knowledge

(SK) and modeling calculations and sensitivity analysis (CUS) is that a student may be able to carry out calculations as an automated process in such a way that it does not depend on his way of thinking. For example, whether a student prefers facts or not, there is only one approach to carry out a regression or solve a particular equation once an engineering model is constructed.

Innate ability (IA) was posited to play a significant role in conceptual changes and one's ability to draw conclusions from a text. Eventually, innate ability influences a students' motivation to work because it controls the extent to which a student believes he can achieve his goal by just trying. In other words, it is a controlling factor of self-efficacy. As a result, we conjecture that it is an overarching factor that controls one's motivation; hence, innate ability can potentially influence all the modeling stages in H_4. We found that for five of the seven modeling stages innate ability (IA) was, in fact, a main effect all with negative coefficients.

Two modeling stages, carrying out calculations (CUS) and validation and verification (VV), had no epistemic dimensions in their models. For the former, CUS, the same explanation that held in simple knowledge also applies; it is possible that the student follows a routine of mathematical steps to calculate the mathematical model, creating low variation in the dependent variable for this data. The extent of human error in calculation is lessened due to the use of software and computers for calculations. The latter, validation and verification (VV), was not observed with sufficient variation to suggest that epistemic beliefs contribute to the outcome; however, because little validation and verification is covered during the sophomore year in industrial engineering, it is still plausible for epistemic beliefs to be significant under other conditions.

Finally, as posited in hypothesis H_5, we did not expect a significant effect of omniscient authority (OA) to appear in any of the models. From Table 3 where the average epistemic beliefs were reported, it is clear that engineering students from all three cohorts were above the theoretical mean indicating that engineering students have higher reliance on authority. However, by design MEAs have minimal instructional guidance, so this dimension may not be a factor for this particular experiment. This statement can be supported since there was no evidence to suggest that omniscient authority was a factor in the models to measure modeling skill development when MEAs are implemented; hence the hypothesis is supported.

Based on the intercepts, sophomore students after four months scored highest on review and evaluation of data (RED). The weakest model is the one for validation and verification stage (VV) of the modeling process. This is not a surprise, as instruction related to validation and verification in modeling at the sophomore level is minimal.

In terms of growth rate, the students have the highest linear growth coefficient in conceptual model development (CON). Identifying the boundaries on the model, stating the assumptions is a practice that is well coined in the sophomore semester. The lowest rate of growth is observed for results evaluation (RE), implying there is not much change in this modeling stage over the two semesters.

5.4.1.2 Impact of Gender, MEA Difference and CGPA

We tested additional models (not shown) to determine whether modeling skill change is a function of gender, specific MEA (Tire Reliability and CNC Machine) or CGPA. These variables were found not to significantly contribute in a systematic manner to the models. Similar to the self-efficacy models tested, effects of these variables vary. In addition, we conducted exploratory analyses to determine if interactions of these variables and the epistemic dimensions (e.g., Gender x Certainty of Knowledge) impacted the model. None of the specified interactions approached significance; and accordingly, we did not include these variables so as not to overcrowd the final models. We did keep them in the analysis of sophomore senior differences, to demonstrate the non-consistent pattern of effects on modeling.

5.4.2 Analysis of Sophomore and Senior Student Differences

In addition to the growth analysis, we conducted a means analysis similar to the analysis of self-efficacy to observe differences in modeling skills at the senior and sophomore levels. We tested the hypotheses given in the theory section using ordinary least squares regression, with each epistemic dimension score as independent variables and the modeling scores (from both the Tire and CNC Machine MEAs combined together) being the dependent variables. The modeling scores were again centered on the mean.

Similar to the growth models, the epistemic dimensions were coded as dummy variables (i.e., students were coded as being either greater or lower than the median for that particular dimension). The resulting regression equation is the following.

$$Y_k = \beta_{0k} + \beta_{1k}Cohort + \beta_{2k}SK + \beta_{3k}CK + \beta_{4k}OA + \beta_{5k}IA + \beta_{6k}QL + \beta_{7k}Gender + \beta_{8k}MEA + \beta_{9k}CGPA + e_k$$

In the model, the variable Y_k stands for each of the modeling stages (where $k=1,2,\ldots 7$, respectively is RED, CON, EPS, CAL, CUS, RE and VV). We differentiate the effect of time with a dummy variable, Cohort, that identifies whether the student is from cohort III, a senior, otherwise, the student belonged to cohort II, second semester sophomores. As mentioned the five dimensions of epistemology (simple knowledge (SK), certain knowledge (CK), omniscient authority (OA), innate ability (IA), and quick learning (QL)) were coded as binary variables. The control variables were gender (binary with 1 = female), MEA (binary with 1 = Tire Reliability MEA), CGPA (continuous variable).

The comparison was conducted using cohort II and cohort III students; and the regression models are given in Table 19.

Table 19. Regression model – comparison of sophomores to seniors with epistemic beliefs

Regression model – Comparison of Cohort II (Sophomore Level) to Cohort III (Senior Level)

Predictors	**Model 3: RED**	**Model 4: CON**	**Model 5: EPS**	**Model 6: CAL**	**Model 7: CUS**	**Model 8: RE**	**Model 9: VV**
	Est. (std.err)	**Est. (std.err)**	**Est. (std.err)**	**Est. (std.err)**	**Est. (std.err)**	**Est. (std.err)**	**Est. (std.err)**
Intercept	3.38 (0.64)***	4.07(0.67)***	4.08(0.56)****	3.52 (0.82)*	2.98 (0.54)***	1.88 (0.77)**	2.46 (0.83)**
Cohort (Seniors)	0.55 (0.19)**	0.72 (0.20)***	1.41(0.17)***	-0.01 (0.25)	0.64(0.16)***	0.97 (0.23)***	0.98 (0.25)**
Simple Knowledge	-0.22(0.20)	-0.13(0.21)	-0.21(0.17)	-0.39 (0.24)*	-0.05(0.17)	0.07 (0.24)	-0.27(0.26)
Quick Learning	-0.39 (0.21)*	-0.37 (0.22)*	-0.32(0.18)	-0.81 (0.27)**	0.11(0.17)	-0.50 (0.25)**	0.06(0.27)
Omniscient Authority	0.02 (0.19)	0.12 (0.20)	-0.04 (0.17)	-0.12 (0.25)	0.02(0.16)	0.19 (0.23)	0.35(0.25)
Innate Ability	-0.43(0.19)**	-0.33 (0.20)*	-0.50 (0.16)**	-0.38 (0.24)*	0.02(0.16)	-0.67 (0.22)***	-0.22(0.24)
Certain Knowledge	0.17 (0.20)	0.33 (0.24)	-0.30 (0.18)*	0.14 (0.26)	0.23(0.17)	0.03 (0.25)	0.24(0.27)
Gender (Female)	-0.01(0.22)	-0.01 (0.23)	-0.04 (0.19)	0.13(0.28)	-0.33(0.18)*	0.17 (0.27)	-0.00 (0.29)
CGPA	0.25 (0.21)	-0.02 (0.22)	0.05 (0.18)	0.34(0.28)	0.28(0.18)	0.38 (0.26)	-0.22(0.28)
MEA (Tire)	-0.10(0.18)	-0.36(0.19)*	-0.22 (0.15)	-0.69 (0.23)**	0.09(0.15)	0.25 (0.21)	-0.61(0.23)**
R^2	0.16	0.16	0.41	0.19	0.16	0.22	0.15
F-value	3.07	3.24	11.57	3.83	3.22	4.66	2.96
Degrees of Freedom	9	9	9	9	9	9	9
P-Value	p<0.01	p<0.001	p<0.001	p<0.001	p<0.001	p<0.001	p<0.01

***denotes p<0.01; **denotes p<.05; *denotes p < 0.10.

When we investigate the impact of the different epistemic dimensions, we again observe, as hypothesis H_5 posited, that omniscient authority has no significant effect on any of the models. In particular, we find that the effects of quick learning (QL) appear in several of the models, and that innate ability (IA) is also prevalent in several of the models. It does appear that these two variables, coupled with the prior results with the growth models, do influence learning of modeling abilities.

Although the regression models were all significant as measured by the F-value, their R^2 values were relatively low with the exception of the EPS model (R^2 = 0.41). This value is relatively a decent value. This suggests that there is indeed a strong change in being able to identify the goals of a given exercise from the sophomore to senior year. It is possible that this improvement is correlated with increasing experience and feedback students received over the years in their education. Being able to identify the goals is practiced in each exercise, project or homework that a student completes, regardless whether it involves a model or not. And if students fail to correctly identify the goal, they receive negative feedback through their grades. Therefore, students have many more chances to practice goal identification compared to the other modeling stages. This might imply the strength of modeling skill development for seniors in comparing the two cohorts.

The low R^2 values for the other modeling stages are somewhat expected as the independent variables were categorical in nature. With that said; the impact of epistemology on the models does warrant discussion as there were a few similarities to the growth models. The two commonly significant effects were the intercept, and resembling the Months variable in the growth model, the cohort variable. The coefficients for the cohort variable were positive and significant with the exception of the CAL model, suggesting that growth did occur in the modeling stages from sophomore to senior year. The highest cohort coefficient is in the Establishing the Performance Criteria (EPS) dimension. A student with sophisticated epistemic beliefs could potentially reach over 5.4 points out of the maximum level six (4.08+1.41+ impact of epistemic dimension), which suggests that for this stage of modeling students are well developed by the end of the sophomore year. The least significant improvement based on seniority level was observed for Development of Calculational Model (CAL), and despite insignificant, reversing the pattern, had a negative cohort coefficient, implying that sophomores might be better in this area. The reason why this reversal effect is taking place might be related to the MEAs requiring statistical knowledge, and statistics knowledge is fresher in the minds of sophomores (due to curriculum and instruction), compared to the seniors.

For the control variables, gender effects are only present and to the disadvantage of female students for the model Calculations and Sensitivity Analysis (CUS). It is recognized in the mathematics literature that females tend to have lower self-efficacy than males. This could possibly be the reason for the presence of this variable in this model. Cumulative GPA was not a significant effect in any of the models, which is possible since the assessment of modeling in this experiment was independent of the GPA (i.e., the CGPA was based on the semester prior to the MEA implementation). Finally, the Tire MEA appeared in three of the models with a negative coefficient indicating that the participants found this MEA to be more challenging than the other MEA.

5.5 SUMMARY OF STUDY 2

The role of epistemological beliefs of learning is both subtle and ubiquitous. This study is aimed at understanding the impact of students' epistemic perspectives on their modeling skills. In doing so, we provided a summary of the epistemology literature and theorized the impact of epistemic beliefs on engineering modeling. We collected data from sophomore and senior engineering students about their modeling abilities and epistemic beliefs by employing MEAs. The results indicate that the majority of engineering students tested are still at a naïve epistemic level across the five dimensions measured.

The statistical information provided by the factor analysis used in this study proved that the EBI, despite lower reliability levels, was capable of illuminating epistemological beliefs from participants. While actual factor loading values differed from the original results reported in Schraw, Dunkle and Bendixen (2002), the obvious similarity of factor loadings (i.e., items to particular factors) demonstrates that the theories behind personal epistemological beliefs can be considered reliable and reproducible.

Table 20 summarizes the overall results of the study. The results demonstrate that the students are indeed negatively influenced on modeling ability development when they have naïve ways of thinking in simple knowledge, certain knowledge, innate ability and quick learning dimensions. Innate ability was one of the most influential beliefs for students, influencing five out of seven stages for the sophomores and seniors. One possible explanation for these results is that students who come to engineering are often more talented, particularly in mathematics, and they may unconsciously developed the idea that one can either “get it”, or not.

Table 20. Summary of All Hypothesized and Observed Effects for Epistemic Beliefs

Epistemic Dimension		Modeling Stages RED	CON	EPS	CAL	CUS	RE	VV
Quick Learning	**Hypothesized Effects (H_1)**	(-)			(-)			
	Sophomore Effect	(-)			(-)			
	Senior Effect	(-)	(-)		(-)		(-)	
	Conclusion	Full			Full			
Certain Knowledge	**Hypothesized Effects (H_2)**				(-)	(-)		
	Sophomore	(+)						
	Senior			(-)				
	Conclusion				None	None		
Simple Knowledge	**Hypothesized Effects (H_3)**	(-)		(-)	(-)	(-)		
	Sophomore	(-)		(-)	(-)			
	Senior				(-)			
	Conclusion	Partial		Part.	Full	None		
Innate Ability	**Hypothesized Effects (H_4)**	(-)	(-)	(-)	(-)	(-)	(-)	(-)
	Sophomore	(-)	(-)	(-)	(-)		(-)	
	Senior	(-)	(-)	(-)	(-)		(-)	
	Conclusion	Full	Full	Full	Full	None	Full	None
Fixed Ability					No effects found			

Note: Epistemic dimension omniscient authority did not have any significant effects on any stage, at both sophomore and senior levels. The sign (-) stands for the negative coefficient.

Innate ability has been shown to be in unison with quick learning, and students who believed in quick learning received lower scores compared to their counterparts, for Review and Evaluation of Data (RED) and Creating a Calculational Model (CAL). Several unanticipated effects were also found. For example, certainty of knowledge (CK) influenced the Review and Evaluation of Data (RED) model. Finally, students preferring factual information (i.e., simple knowledge (SK)) tended to do poorly in Review and Evaluation of Data (RED), setting the goal of the model (i.e., Establishment of Performance Criteria (EPS)), and Calculational Model Development (CAL). This information should not be surprising given that a student who is focused on numerical information would likely not enjoy MEA exercises, preferring textbook examples. Omniscient authority (OA) was not a significant factor, since MEAs are rather autonomous with little instructor involvement. Still, based on the conversations with the students, we can see that during the implementation of MEAs, students exhibited a need for their instructor to be a guiding authority figure to help supply factual information as well as general guidance on methodology. They expressed frustration with the not knowing what to do with some of the given information. The implications of these findings, as well as the suggesting for practitioners and future work is discussed in the overall summary, section 8.1.

6.0 STUDY 3: IMPACT OF METACOGNITION ON GROWTH OF MODELING

6.1 MOTIVATION

Suppose a student is asked to come up with example engineering scenarios for which a particular model can be applied. The first two or three examples may easily come to mind; after that, the task becomes difficult and the student has to search her memory for additional examples. What can an educator conclude from the difficulty the student experienced in coming up with additional examples? Are there no additional ways to apply the model to real life? Is the student's memory for engineering problems poor and her recall is problematic? Or does the student lack the necessary engineering content knowledge relative to the model? Each explanation is plausible and provides a different perspective of the metacognitive link to engineering modeling, i.e., one's monitoring of her memory and actions.

Relative to engineering, teaching a student to become a good modeler requires an understanding of the antecedents and consequences of the process itself, including important behavioral and cognitive influences. In this study, we begin by proposing that the metacognitive characteristics of engineering students can influence the way they approach and model real life systems.

We suggest that an analysis of the metacognitive thinking undertaken in an educational environment will lead to enhanced understanding of the within and between-student differences in learning. We measure students' metacognitive characteristics on four dimensions: (1) self-checking, (2) awareness, (3) planning and (4) cognitive strategy. The rest of the study provides a summary of the research in metacognition, and hypothesizes how metacognition influences modeling. We detail our methodology, and report the findings.

6.2 BACKGROUND

6.2.1 Metacognition and Metacognitive Inventories

Metacognition can be described as a series of thought processes related to planning, monitoring, evaluating and regulating function. According to Flavell (1976), metacognitive knowledge consists of what one learns through experience about cognitive activities; and this knowledge can be categorized into personal, task, and strategy variables. Flavell further notes that a metacognitive knowledge base is critical for successful learning; and that a good learner is one who has ample knowledge about the self as a learner, about the nature of the cognitive task at hand, and about appropriate strategies for achieving academic goals.

Brown (1987) suggested metacognition had two categories: knowledge of cognition (or awareness) and cognitive strategy (which involves reflection on cognitive abilities and activities during the accomplishment of a task); and regulation of cognition (referring to the mechanisms used; e.g., planning, self-checking activities as well as evaluating activities).

Exhibiting metacognitive behaviors implies that one must demonstrate knowledge about herself and her thinking processes; and furthermore, manifest that she can control her thinking process. Studies suggest that cognitive strategies and self-checking behaviors are part of a series of metacognitive behaviors that can enhance learning (Yap 1993, O'Neil et al. 1997). According to Brown, better learners are equipped with a high degree of metacognitive awareness and are able to strategically monitor and evaluate their learning activities. For students, being metacognitive means to be aware of the information needed to accomplish a task, concerning one's attitude and attention to learning new or complex tasks, and the knowledge about the steps, procedures and strategies on how certain tasks are done. Knowing why certain strategies work, when to use them, and why one strategy is better than another are also cues that students are metacognitive (Marzano 1998). Figure 14 provides a list of possible metacognitive strategies, as given by Pulmones (2010), which have been adapted for the MEA tasks.

METACOGNITIVE STRATEGIES FOR STUDENTS
▪ Identifying “what you know and “what you don’t know” ▪ Talking about thinking ▪ Keeping a thinking journal ▪ Planning and self-regulation ▪ Debriefing the thinking process ▪ Self-evaluation ▪ Mind mapping (use of concept maps) ▪ Writing to learn (expository and expressive writing) ▪ Illustrating and drawing ▪ Brainstorming ▪ Generating questions and other inquiry strategies ▪ Portfolio-based assessment

Figure 14. Metacognitive strategies for students

6.2.2 Metacognition and Model Eliciting Activities (MEAs)

MEAs are activities that are designed to help students link their prior knowledge and construct new knowledge as they engage in a modeling exercise, thereby helping them to learn the identified topics (Lesh, Lester, and Hjalmarson, 2003, Chalmers 2009, Chan 2008). MEAs can be constructed around various engineering topics and force students to think, control and self-assess their thinking as they perform modeling tasks, activating their metacognitive abilities. Students engage in these activities both on their own and within their team, linking their prior knowledge to reinforce what they already know. Following the modeling activity, students reflect on their thinking about how they modeled the activity. Hence, as students engage in an MEA, they engage in each of the four dimensions of metacognition, namely, awareness, self-checking, cognitive strategy, and planning. We have provided a list of the metacognitive tasks adapted from Pulmones (2010) for the dimensions of O'Neill and Abedi (1996) in Figure 14; Figure 15 gives a list of the expected behaviors in the four major dimensions of metacognition.

Metacognitive Dimension	**Possible Metacognitive Behaviors**
Cognitive Strategy	▪ Thinking / deciding on the multiple ways of solving the MEA ▪ Comparing the different ways of modeling the problem and deciding on which one(s) to pursue
Planning	▪ Choosing and writing the purpose/ goal of the model, or the performance criteria ▪ Listing the tasks to be carried to get to the performance criteria ▪ Identifying how to do the search functions for the information that is necessary to build the model ▪ Planning on the schedule / time for carrying out the modeling tasks
Awareness	▪ Realizing the ongoing thinking processes that take place during modeling ▪ Identifying the reasons for the thinking process that is taking place and relationship to the knowledge attained
Self-checking	▪ Evaluating the performance criteria to decide if the purposes of constructing the model are met ▪ Reflecting on modeling strategies that worked and did not work ▪ Assessing how the developed model can be applied in other learning context ▪ Rewarding self after constructing the model

Figure 15. Metacognitive dimensions and example manifestations

MEAs provide students with opportunities to practice their metacognitive abilities. The difficulty of modeling could affect students' metacognitive behavior and learning; further, the time allotted for the completion of tasks could also influence students' demonstration of their metacognitive behaviors. If students can reflect on their thinking as they plan, monitor and evaluate their learning, they can influence the development of modeling abilities. In the next section, we develop more specific predictions as to how students' metacognition is linked to modeling skill development.

6.3 THEORY

6.3.1 Impact of Metacognition on Modeling Skill Development

Of special importance is the way in which metacognition adds to modeling skill development. The dimensions of metacognition, as enumerated in the measurement instrument we used are (a) *awareness*, (b) *self-checking*, (c) *cognitive strategy* and (d) *planning*. We describe each of these dimensions below and hypothesize how we expect them to influence the development of modeling ability.

6.3.1.1 Awareness

Awareness implies that one is conscious of her ongoing thinking processes (O'Neil and Abedi 1996). Awareness is a higher order and vague construct, and is different from the other metacognitive dimensions in that it is an ability to execute metacognitive monitoring along with working on the task itself. It is not uncommon that a student, focusing on the physical or cognitive efforts of a task, fails to take time to separately consider the questions that are related to understanding the thinking process itself. Therefore, even though one would expect metacognitive awareness to execute properties that can help develop modeling skills, in reality, we expect that awareness will be less influential, or will not be observed as a significant factor. Hence, the first hypothesis:

> ***H_1*:** *Awareness does not have an observable impact on the development of engineering modeling skills at the undergraduate level.*

6.3.1.2 Self-Checking

Self-checking ability implies students' ensuring that the work is carried out according to the goals of the study and is correctly conducted. One would expect that this would be key to developing better modeling skills, as checking one's work on a regular basis is not only making sure the task is completed to expectations, but is also providing instant feedback about what is learned and how it is working. In fact, such ability should be the key in developing modeling abilities. Therefore, our second hypothesis is:

H_2: *Higher self-checking ability results in development of better engineering modeling skills compared to students with lower ability to self-check.*

6.3.1.3 Cognitive Strategy

Cognitive strategy is defined as the ability to use multiple thinking techniques or strategies to model a system. This ability enables the student modeler in several ways. First, due to awareness of multiple techniques, the student can have more and better ways to construct the mathematical model. Second, these multiple methods can enable the student to see more scenarios related to the model and double check the results using different methods. However, without sufficient domain knowledge of multiple techniques, this may not occur. For example, if a student only knows how to draw histograms to decide on the fit of a distribution, then she is likely to be limited in the cognitive strategies she can use to approach a problem. In contrary, once the student learns about chi-square goodness of fit tests, she is more likely to double check the distribution using the two techniques.

Therefore, we expect that the cognitive strategy will become a moderator of the effect of modeling experience, or time, on development of modeling ability. Specifically, we expect that the higher the cognitive ability of the student, the better she will be in modeling; and this effect will be more pronounced for more experienced students. This leads to our third hypothesis, which has two parts:

H_{3a}: *Higher cognitive strategy results in the development of better modeling skills compared to students with lower cognitive strategy.*

***H_{3b}*:** *Cognitive strategy positively moderates the impact of experience on the development of modeling skills. Specifically, the higher the cognitive strategy of a student and the more experienced he is in modeling, the higher is the modeling growth.*

6.3.1.4 Planning

Planning stands for one's attempt to first understand a task before working on it. In the modeling context, planning would refer to understanding what needs to be done and how it should be done, i.e., planning the actual modeling process itself. When a student is a better planner, it is likely that she will be better in allocating the right amount of time and tasks to the process, resulting in better outcomes. In return, a positive outcome would itself feed the learning process.

Similar to cognitive strategy, however, planning is also likely to become more effective over time. However, without testing how a plan works, or actually experiencing the task a few times, even if planning occurs, it might not be effective. Specifically, we expect that the better the planning ability of a student, the better she is in modeling, and that this effect is more prominent for more experienced students. This leads to our last hypothesis, which also has two parts:

***H_{4a}*:** *More advanced planning results in the development of better modeling skills compared to students with lower planning abilities.*

***H_{4b}*:** *Planning positively moderates the impact of experience on the development of modeling skills. Specifically, the more advanced planning ability and more experience, together, will result in higher modeling ability.*

6.3.2 Metacognition and MEAs

Using the descriptions of the modeling exercises, Figure 16 and Figure 17 provide examples of the metacognitive properties of MEAs. A description is given of the metacognitive activities that were observed while students solved the Tire and CNC Machine MEAs.

Metacognitive Activity	Description (related metacognitive dimension)
Nature, Purpose and significance of Model Eliciting Activity	Students were asked to determine if the tires from different manufacturing batches are reliable. Students first determined what it means to be reliable (self-checking), and then decided on how to measure reliability (cognitive strategy and self-checking). Students determined the purpose of the exercise, and then decided on what information, data and techniques to use to analyze data (planning).
Determination of Performance Criteria	Using the analysis of the data, students determined what quantities to measure and use to identify reliability (cognitive strategy). This involved thinking about what students know (self-checking, awareness), how they can use what they know (planning), and how they can interpret what they derive (self-checking).
Analysis, Modeling and Reporting	Using analysis, students identified the distributions of the data, and whether the variance in the data is small enough to consider the batch reliable (cognitive strategy, self-checking). In teams, students discussed how to model the problem (self-checking). Students verbalized and wrote about their thinking (planning, self-checking).

Figure 16. Examples to metacognitive activities during the Tire MEA

Metacognitive Activity	Description
Nature, Purpose and significance of Model Eliciting Activity	Students were asked to decide if the investment into a new CNC machine is justifiable (awareness, self-checking). Students determined from a given data set which machine is better, and whether the investment was worthy (planning, cognitive-strategy).
Determination of Performance Criteria	Using the analysis of the data, students determined whether the new machine was better than the current one (cognitive strategy). This step, again, involved thinking about both what students know (awareness), how they can use what they know (planning), and how they can interpret what they derive (self-checking).
Analysis, Modeling and Reporting	Using analysis, students identified the distributions of the data (self-checking), tested the difference, and decided on break-even points to consider the investment worthy (cognitive strategy, self-checking). In teams, students discussed how to model the problem (self-checking). Students verbalize and write down their thinking (planning, self-checking).

Figure 17. Summary of metacognitive activities of the CNC Machine MEA

Teams of students solved the two MEAs, which were of similar level of difficulty as assessed by the faculty who implemented them in their sophomore classes. As students solved the MEAs, they discussed their answers with team members, and wrote about their methodology, allowing them to be conscious of their own thinking and modeling process, thus demonstrating the metacognitive behaviors that are listed in the figures.

6.4 ANALYSIS

6.4.1 Analysis of Metacognition Impact: Sophomore Year Change

Similar to the other two studies, to analyze the potential longitudinal changes that took place during the sophomore year (i.e., two semesters), we used a random coefficients model. However, this model measured the overall change in modeling, as measured by the sum of all seven modeling stages, as opposed to developing a separate model for each modeling stage. This approach is followed deliberately to provide the reader with a more complete picture of the change in modeling, in addition to the micro pictures provided in sections 4.5.1.1 and 4.5.1.2.

The unconditional means model, an unconditional linear model and an unconditional nonlinear growth model were fit first. The results were then used to build the foundation for subsequent analyses as per Singer and Willett (2003).

6.4.1.1 Unconditional Means Model

We estimated a two-level model not including any predictors, captured in the following form:

Level 1: $Y_{ij} = \beta_{0j} + e_{ij}$,

Level 2: $\beta_{0j} = \gamma_{00} + \delta_{0j}$.

In this model, Y_{ij}, the i^{th} month modeling skill level of the j^{th} student, is a linear function of a grand mean (γ_{00}), a deviation of the j^{th} student from the grand mean (δ_{0j}), and a random error term associated with the skill level of the i^{th} month of the j^{th} student (e_{ij}). The model decomposes the variation of modeling skill development into the variation between student means (τ_{00}), and the variation among months within the students (σ^2) (Singer 1998).

Similar to Littell et al. (2006), a maximum likelihood estimation approach was used. The model converged after two iterations. The covariance parameter estimates show that the estimated value of τ_{00} is 22.74 and that of σ^2 is 5.4. Both variance components are significantly different from zero. The estimated intra-class correlation ρ is

$$\hat{\rho} = \frac{\hat{\tau}_{00}}{\hat{\tau}_{00} + \hat{\sigma}^2} = \frac{22.74}{22.74 + 5.4} = 0.80.$$

The 0.80 derived correlation suggests that substantial variation of modeling skill development exists between students and thus the ordinary least squares (OLS) assumption that all observations are statistically independent from one another is likely violated (Berry 1993). Such violation may lead to biased estimates and justifies the usage of a growth curve modeling approach (Bliese 1998).

6.4.1.2 Unconditional Linear Growth Model (Model 1)

Following the means model, we then introduced the variable time (i.e., months) and fitted an unconditional linear growth model. The level 1 equation estimates the individual student's trajectory of modeling growth (β_{1j}) in addition to the mean (β_{0j}). The level 2 equation simultaneously partitions the two estimates into sample averages and error components.

Level 1: $$Y_{ij} = \beta_{0j} + \beta_{1j}Month_{ij} + e_{ij},$$

Level 2: $$\beta_{0j} = \gamma_{00} + \delta_{0j},$$

$$\beta_{1j} = \gamma_{10} + \delta_{1j}.$$

The month variable ranges from 1 to 8 and represents the number of months since the sophomore academic year started. The variable was mean-centered; thus, the intercept reflects the modeling level of a student midway through the 8 month academic year. Note that the modeling stage outcomes were not mean-centered. The SAS Proc Mixed procedure (Version 9.2) generated the results given in Table 21.

Table 21. Individual Growth Models for Longitudinal Growth in Modeling- Sophomore Year

Individual Growth Models for Longitudinal Growth in Modeling- Sophomore Year							
Predictors	**Unconditional Means Model Est. (std.err)**	**Model 1: Unconditional Growth Est. (std.err)**	**Model 2: Nonlinear Unc. Growth Est. (std.err)**	**Model 3: Awareness Est. (std.err)**	**Model 4: Self-checking Est. (std.err)**	**Model 5: Planning Est. (std.err)**	**Model 6: Cognitive Strategy Est. (std.err)**
Intercept	19. 15 (0.4)***	19.24(0.39)***	20.65(0.54)***	20.93(0.56)***	20.90(0.55)***	20.91 (0.56)***	20.93(0.56)***
Months		1.6(0.16)***	1.74 (0.17) ***	1.77 (0.18)***	1.77 (0.18)***	1.76 (0.18) ***	1.77 (0.18)***
Months^2			-0.22 (0.06) ***	-0.25 (0.061)***	-0.25 (0.061)***	-0.25 (0.07)***	-0.25 (0.061)***
Awareness				0.42 (0.26)			
Awareness x Months				0.11 (0.08)			
Awareness x Months^2				-0.04 (0.03)			
Self-checking					0.50 (0.22)**		
Self-checking x Months					0.10 (0.07)		
Self-checking x Months^2					-0.03 (0.02)		
Cognitive Strategy							0.47 (0.23)*
Cognitive Strategy x Months							0.07 (0.06) *
Cognitive Strategy x Months^2							-0.05 (0.03)
Planning						0.41 (0.22)*	
Planning x Months						0.10 (0.06)*	
Planning x Months^2						-0.04 (0.02)	
Fit Statistics							
-2 Log Likelihood	1271.5	1213.8	1200.5	1040.7	1037.5	1039.7	1039.8
Model Fit	p<0.001	p<0.001	p<0.001	p<0.001	p<0.001	p<0.001	p<0.001

Note. ***denotes p<0.01; **denotes p<.05; *denotes p < 0.10. Sample size is 39 with four time points.

Fixed Effects. As shown in Table 21 Model 1, the intercept is 19.24, and slope is 1.6. The intercept is the estimate of the average modeling level roughly at the end of the first sophomore semester, and the slope is the estimate of the average slope across students (i.e., the average growth per month). Hence, the average student achieved 19.24 (out of 42) points on the modeling rubric four months after the semester started, and on average, she increased her modeling skill level by 1.6 points per month. Both null hypotheses that these parameters are zero in the population were rejected.

Random Effects. We then focused on the random effects by examining the variance-covariance components. As variance components of both intercept and slope are significant, we concluded that there exists variation that potentially could be explained by student-level variables (Singer 1998). We further examined this notion by fitting the data into a simplified model. This model had both fixed and random effects on the intercepts but only a fixed effect on the slopes. We then used goodness-of-fit indices to compare these two models. The indices show that the random-slope model is a better fit because -2Log Likelihood is much smaller. Based on these results, we chose random-slope models for all subsequent analyses ($\Delta\chi^2 = 57.7$, d.f. = 1, $p < .001$).

6.4.1.3 An Unconditional Nonlinear Growth (Model 2)

Following the analysis of the linear growth model, we tested a nonlinear model by adding a quadratic term (the squared mean-centered months); the results supported this nonlinear growth model. This testing is given as well in Table 21.

Compared to the unconditional linear growth model, the unconditional nonlinear growth model was significantly better based on the incremental chi-square criterion ($\Delta\chi^2$ = 13.5, d.f. = 1, p <.001). In addition, intercept, linear and quadratic time variables were all significant at the 0.05 level. Therefore, for the rest of the analyses, the unconditional nonlinear growth model was used as the base model.

6.4.1.4 Conditional Nonlinear Growth with Awareness (Model 3)

After selecting the unconditional nonlinear growth model with random effects, we added the student -level predictor (i.e., students' awareness) to investigate whether the intercepts and linear and nonlinear slopes of modeling performance growth vary as a function of these variables. These results can then be used to test the hypotheses that awareness has no effect on modeling ability development. The models are as follows:

Level 1: $$Y_{ij} = \beta_{0j} + \beta_{1j} Month + \beta_{2j} Month^2 + e_{ij},$$

Level 2:

$$\beta_{0j} = \gamma_{00} + \gamma_{01} Awareness + \delta_{0j},$$

$$\beta_{1j} = \gamma_{10} + \gamma_{11} Awareness + \delta_{1j}.$$

As in the unconditional models, only the linear and quadratic terms of the time variable (i.e., months and squared months) were included in the level 1 equation. However, in the level 2 equations, we included awareness as the student-level predictor. To ensure that the fixed effects can be interpreted properly, we centered the student level predictors at mean zero (Singer 1998). Thus, in this model, γ_{00} represents the average intercept in the individual growth model, whereas γ_{10} represents the average slopes of the linear term.

The proposed hypotheses would be tested by examining the coefficients in the level 2 equations corresponding to the student-level variables. For example, the signs and significance of γ_{01} and γ_{11} reflect the impact of a student's awareness on the modeling level and growth trajectory of the modeling skills, respectively.

The results are reported in Table 21. As posited in hypothesis H_1, we did not expect a significant effect for awareness on the modeling ability development. In fact, we found that for this hypothesis there was not enough evidence to suggest that awareness was a significant factor in modeling development. Additionally, we tested its impact on the growth trajectory; again, no significant effects were observed.

6.4.1.5 Conditional Nonlinear Growth with Self-Checking (Model 4)

Subsequently, we added the self-checking dimension of metacognition to further investigate whether the intercepts and linear and nonlinear slopes of modeling performance growth vary as a function of these variables. These results then could be used to test the hypotheses that self-checking has a significant impact on modeling ability development. The models are as follows:

Level 1: $$Y_{ij} = \beta_{0j} + \beta_{1j} Month + \beta_{2j} Month^2 + e_{ij},$$

Level 2:

$$\beta_{0j} = \gamma_{00} + \gamma_{01} Self - checking + \delta_{0j},$$

$$\beta_{1j} = \gamma_{10} + \gamma_{11} Self - checking + \delta_{1j}.$$

Similar to the previous models, in the unconditional models, only the linear and quadratic terms of the time variable (i.e., time in months and months squared) were included in the level 1 equation and in the level 2 equations, we included self-checking as the student-level predictor. Similar to before, we centered self-checking at its grand mean (Singer 1998), implying that model, γ_{00} represents the average intercept in the individual growth model, whereas γ_{10} represents the average slopes of the linear term.

The results are again reported in Table 21. As posited in hypothesis H_2, we did find a significant positive main effect for self-checking on development of modeling ability. This hypothesis was supported by the fact that $\gamma_{10} = 0.5$ (p < 0.0001). This positive and significant coefficient suggests that, holding all other variables constant, when self-checking increases by one unit, the score on the development ability on average increase by 1.77 points. In addition, the cross-level interaction was not significant indicating that students' self-checking does not significantly change the growth trajectory. Therefore we found support for hypothesis H_2. We also tested for the moderation effect of self-checking, but there was no evidence to suggest that self-efficacy moderated the growth trajectory.

As in Table 21, Model 3, which consists of student's self-checking as the level 2 predictor, has a -2 Log Likelihood of 1037.5. With two degrees of freedom, the incremental Chi-square was statistically significant ($\Delta\chi^2 = 63$; $p < 0.0001$) when compared to Model 2, the unconditional nonlinear model, thus justifying the inclusion of student's self-checking and providing additional support for H_2.

6.4.1.6 Moderation Analyses of Planning (Model 5)

We then repeated the process of simple slope analysis by using planning (Model 5) as a main factor and the moderator of time. The results are reported in Table 21, which depicts the impact of student's planning on modeling skill trajectory. Specifically, a student who reported a high planning level obtained 0.41 points more than another student who had a lower planning level, and the growth trajectory was faster (0.1 points) than a student who had lower planning level. This implies that when a student is higher on the planning skills for one point, her pace of development is increasingly over time, compared to the student with lower planning skills, reaching a 0.8 difference at the end of the two semesters. It is possible to interpret this moderation impact from the time perspective. A student who had a one point advantage over another student in planning reached a higher modeling skill level earlier within the year than did the other student. In contrast, the low planning counterparts spent extra days to close the gap. These results support H_{3a} and H_{3b}.

6.4.1.7 Moderation Analyses of Cognitive Strategy (Model 6)

Similar to the previous section, we then repeated the process of simple slope and moderation analysis by using cognitive strategy (Model 6) as the moderator. The results are reported in Table 21, which depicts the impact of students' cognitive strategy on modeling trajectory. In particular, for each unit of difference in cognitive strategy, students are observed to have a higher score of 0.47 unit, in addition to having a trajectory that is more upward trend. These results support H_{4a} and H_{4b} that state that cognitive strategy has a significant main effect and a significant interaction term with time.

6.4.1.8 Impact of Gender, MEA Difference and CGPA

In addition to the six models developed, we also developed and tested models to determine whether modeling skill change is a function of gender, the specific MEA or cumulative GPA. The impact of these variables did not improve upon or change what was learned from the previously developed models on metacognition. Therefore, the reported models excluded the effect of these variables not to overcrowd the model.

6.4.2 Analysis of Sophomore and Senior Differences

In addition to the growth analysis, we conducted a means analysis to determine the differences between senior and sophomore levels. The comparison was made to account for the changes that take place after having finished the senior year; therefore, the data consisted of cohort II and cohort III. We tested the same hypotheses, with each dimension score being the independent variable and the modeling scores (from both the Tire and CNC Machine together) being the dependent variable, as given in the equations below. Interaction terms were kept in the analysis for completeness. In these equations, cohort is a dummy variable that determines whether the student belongs to cohort II (sophomore, cohort=0) or cohort III (senior, dummy=1).

$$Y_i = \beta_0 + \beta_1 Cohort + \beta_2 Awareness + \beta_3 Awareness \ x \ Cohort + \beta_4 Gender + \beta_5 CGPA + \beta_6 MEA + e_i,$$

$$Y_i = \beta_0 + \beta_1 Cohort + \beta_2 Selfchecking + \beta_3 Selfchecking \ x \ Cohort + \beta_4 Gender + \beta_5 CGPA + \beta_6 MEA + e_i,$$

$$Y_i = \beta_0 + \beta_1 Cohort + \beta_2 Planning + \beta_3 Planning \ x \ Cohort + + \beta_4 Gender + \beta_5 CGPA + \beta_6 MEA + e_i,$$

$$Y_i = \beta_0 + \beta_1 Cohort + \beta_2 CogStrategy + \beta_3 CogStrategy \ x \ Cohort + \beta_4 Gender + \beta_5 CGPA + \beta_6 MEA + e_i,$$

The overall modeling scores were again centered at the mean. The results of the regression models are given in Tables 26. We found two significant main effects that hold for all models; specifically, both intercept and being a senior have significant positive coefficients. In particular, seniors appear to score in the range of 4.03 to 5.02 units better than the sophomore second semester students. The R^2 values, as expected are small, since there are multiple factors like gender, type of MEA and cohort that are categorical, yet all models are significant according to the F-value.

Table 22. ANOVA- Sophomore to Senior Change when Metacognitive Effects are Included

Predictors	**Model 7: Awareness Est. (std.err)**	**Model 8: Self-checking Est. (std.err)**	**Model 9: Cognitive Strategy Est. (std.err)**	**Model 10: Planning Est. (std.err)**
Intercept	15.46 (4.04) ***	17.21 (3.99) ***	16.98 (4.06)***	18.61 (3.69) ***
Cohort (Senior)	4.32 (1.13) ***	5.02 (1.11) ***	4.52 (1.11) ***	4.03 (1.14) ****
Awareness	0.39 (0.32)			
Awareness x Cohort	0.37(0.48)			
Self-checking		0.57 (0.27)*		
Self-checking x Cohort		-0.30 (0.36)		
Cognitive Strategy			0.13 (0.3) *	
Cognitive Strategy x Cohort			0.72 (0.42) *	
Planning				0.51 (0.27) *
Planning x Cohort				0.31 (0.44)
Gender	0.42 (1.19)	0.58 (1.19)	0.45(1.20)	0.79 (1.19)
CGPA	1.95 (1.29)	1.29 (1.27)	1.40 (1.28)	2.09 (1.26)
MEA	1.68 (1.04)	1.68 (1.04)	1.68 (1.03)	-1.68 (1.03)
R- square	0.20	0.20	0.21	0.21
Model F-value	6.86	6.18	6.67	6.86
P-Value	p<0.0001	p<0.0001	p<0.0001	p<0.0001

***denotes p<0.01; **denotes p<.05; *denotes p < 0.10.

As posited in hypothesis 1, awareness, once again failed to show a significant impact on the level of modeling, both as a main effect and as a moderator (Model 7). Therefore, even for the seniors, awareness is not a distinctive factor. For self-checking, we found a similar effect on the change observed at the sophomore level. In particular, we found that a single unit change in the self-checking results in 0.57 unit change in the modeling score (Model 8). When seniors and sophomores were compared, cognitive strategy did not repeat as a significant main effect, but did have a higher significant term (Model 9). In particular, being a senior implied having a higher score on modeling compared to a lower level student with the same cognitive strategy score, or the student with a higher cognitive strategy implied that she had a better score when both students came from the same cohort. That is, the impact of cognitive strategy strengthened with time. In particular, if a student was a senior, she had 0.72 average score in modeling for every incremental point of cognitive strategy.

Finally, for planning, we found a significant main effect on the modeling score. The students obtained a 0.57 higher modeling score for each incremental point in modeling (Model 10). The interaction term was not significant, implying that planning has an overall impact on both cohorts, and being a senior does not imply this effect, alone, is significantly stronger. Accordingly, we find support for hypotheses 1, 2, 3b and 4a. As demonstrated in the table, when the metacognitive effects are already accounted for, gender, cumulative GPA (CGPA) and type of MEA did not have significant effects on modeling score.

6.5 SUMMARY OF STUDY 3

In this study, we aimed to achieve the following goals: decide on the metacognitive properties of MEAs, and decide on the role of metacognitive dimensions on development of modeling skills. Collecting data from sophomore and senior engineering students on their modeling levels and metacognitive properties, we have determined the impact of metacognition on modeling. We find that MEAs show metacognitive properties for engaging students to think about what they have learned, and how they can use it.

Difficulty in learning how to conduct and understand engineering modeling can be a function of having poor initial domain knowledge, as well as difficulty in not being able to connect one's thinking process to domain knowledge and to implementation. When students engage in an effort to: (1) think about formulating a model to solve a problem, (2) explain their modeling strategy to group members verbally, and (3) write about their model, they strengthen their discussions. Students are more likely to retrieve discussions of modeling principles from long-term memory and thus strengthen those memories. In addition, they may consult books and the internet to find verbal descriptions of other modeling examples, and thus strengthen this knowledge. Sharing their information with group members, or observing that a method does not work as intended, students can also correct their misconceptions and incorrect knowledge.

In this work, we aimed to answer the question about the degree to which metacognitive properties influence a student's modeling skill change. By using a growth model, we observed that three of the four dimensions of metacognition (namely planning, cognitive strategy, and self-checking) had a significant impact on the modeling change.

Figure 18 summarizes the assessment that is carried out for the growth model. In Figure 18, the four dimensions of metacognition are demonstrated with the circles, as well as the experience. The experience in the figure refers to more than just time effect, but instruction, as well as maturation of the student. The overall concave curve shows the direction and trajectory of modeling growth. The arrows, regardless of where they intersect this curve, show that there is a significant main effect of the variable to modeling ability growth. The arrows that go to experience and then to the curve imply that the interaction term of time and the construct are significant. The figure implies that self-checking and experience have the stronger effects on development of modeling ability.

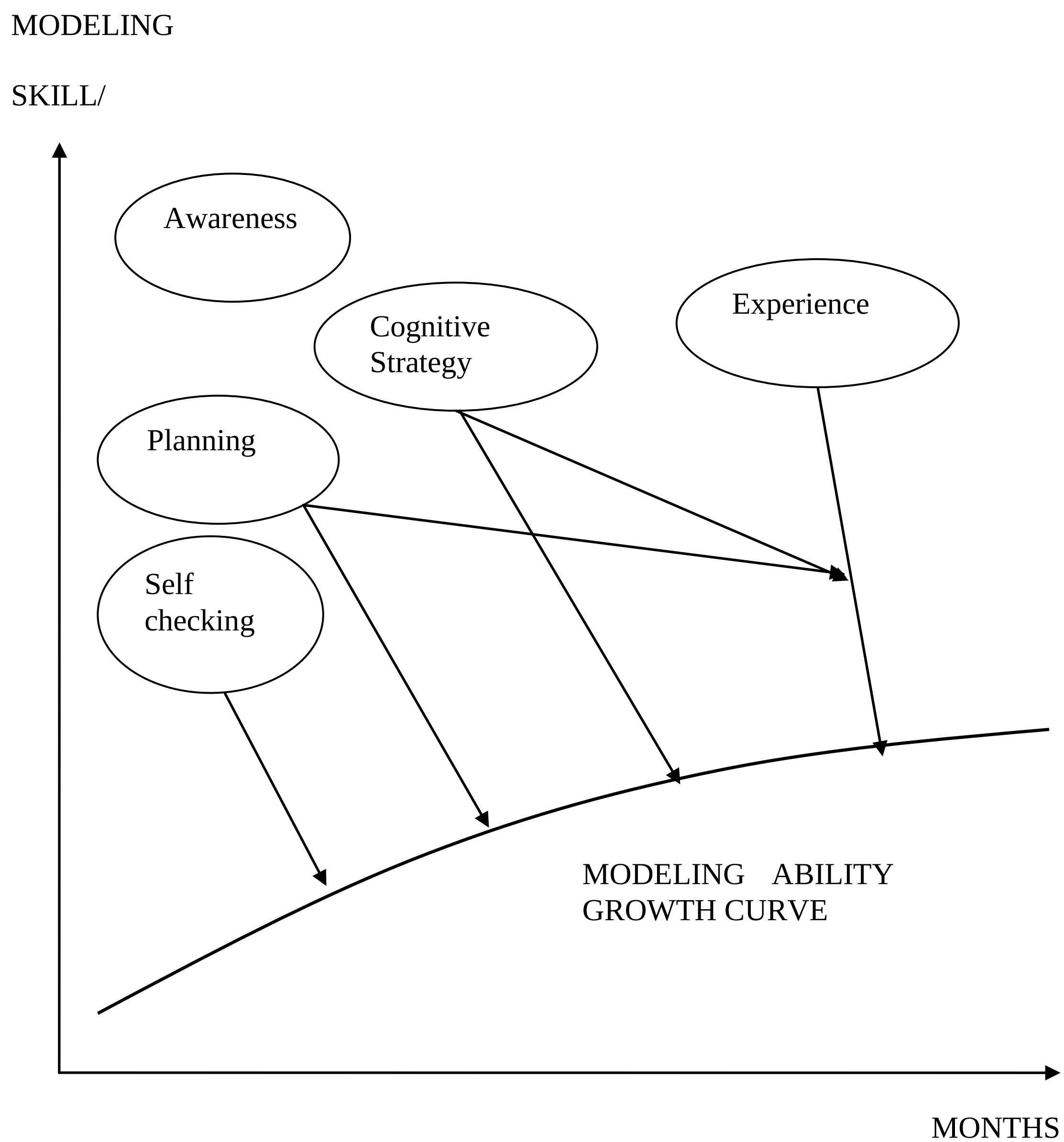

Figure 18. Conceptual framework of metacognition effects on modeling growth

The testing conducted on sophomores demonstrated that students who show higher metacognitive abilities are better or faster in developing modeling skills, as measured by their MEA report scores. We observe that students who scored higher on self-checking, planning and cognitive strategy scored higher on their modeling ability over the course of two semesters, compared to students with lower skills. In particular, students with higher scores on planning and cognitive strategy had a more upward sloping growth trajectory, implying that it took them less time to gain a desired level of modeling ability or they had higher scores after the same time period, compared to their lower metacognition level counterparts. We did not observe the same impact for awareness. Further, at the senior level the results we found were repeated to a large extent. In particular, we found that self-checking and planning retained their significant positive main effect, and cognitive strategy had a strong significant effect on the senior students. Awareness, once again, did not result in significant coefficients.

7.0 STUDY 4: QUALITATIVE ANALYSIS OF MODELING CHANGE

7.1 MOTIVATION

In this study, grounded in the empirical findings we present how students develop in engineering modeling, as they matriculate through their engineering programs. To do this, we explore modeling practices of different levels of engineering students using a qualitative methodology. Cohorts of sophomore and senior students were asked to provide written solutions; an open-ended interview with the team then followed. These solutions and interviews were then evaluated using a number of factors for quality in modeling. This section is added to the dissertation to provide further justification for the modeling growth, and to provide a discussion to help practitioners who are not in the field of engineering, but interested in engineering education. This study thus aims to contribute to the dialogue on engineering modeling by creating a descriptive framework on changes that take place during undergraduate engineering education, with the long term goal of aiding instructors in understanding development of modeling skills.

7.2 ANALYSIS

7.2.1 Response Coding

Participants' transcribed interviews were analyzed according to a coding scheme, listed in Table 23, which provided for each modeling stage the many different approaches students could use along with the desirable educational outcome; hence, the corresponding behaviors were graded relative to level of sophistication.

The researcher analyzed each interview for evidence of the presence of desirable modeling skills. For example, any indication or reference of an alternative modeling method was considered as evidence of multiple thinking. Similarly, an assumption related to modeling was regarded in evaluating students' conceptual modeling process. Additional qualitative analyses focused on analyzing the various modeling strategies that were executed to capture the richness and depth of participants' modeling skills. A single researcher conducted the coding of the transcripts.

Based on these categories, an analysis of the desirable modeling skills was conducted and summarized in Table 24. We have commented on the desirability of the modeling outcomes given in this table.

Table 23. Classification of modeling approaches students used

Classification of Modeling Approaches

Category	Possible Approach	Classification
1. Review and Evaluation of Data		
	Visual / Graphical observation	Less sophisticated
	Scatter plots	
	Histograms	
	Box-plots	
	Numerical analysis of the data	
	Calculation of mean	More sophisticated
	Calculation of standard deviation	
	Calculation of other descriptive stats (skewness etc.)	
2. Conceptual Modeling- *Creation / checking assumptions and restrictions to simplify the real world problem*		
	Checking data distribution	More Sophisticated
	Probability plots	
	Ryan Joiner Normality Test	
	Chi-square goodness of fit test	
	Creating assumptions related to data	
	Assumption of reliable data	
	Assumption of Normality	
	Assumption related to simplification of real life	More Sophisticated
	Assumptions related to expected work from them	Less sophisticated
3. Establishing the Performance Criteria/ *Understanding the goal of the Problem*		
	Recognition of problem goals and establishment criteria	More Sophisticated

Table 23 (Continued)

Category	Possible Approach	Classification
4. Development of Mathematical Model- *Comparison of data sets*		
	Visual comparison	Less sophisticated
	Probability plots	
	Eye-balling	
	Numerical comparison	More Sophisticated
	Hypothesis testing	
	Confidence interval	
	ANOVA	
	Comparison of failure rates	
	F-tests	
	Quality control chart	
5. Carrying out Calculations and Uncertainty analysis		
	Calculations	A combination of all tasks is the most sophisticated
	Sensitivity analysis	
	Recognizing data uncertainty	
	Checking outliers	
6. Results Evaluation & Reporting		
	Memo writing	
	Process description clarification focus	Providing both analysis is the
	Process justification focus	
	Presentation	N/A
7. Validation/ Verification		
	Face validity	Less sophisticated
	External validity	More sophisticated
	Verification	More sophisticated

Table 24. Modeling Categories, Ideas, and Desirable Modeling Outcomes

Category	Definition	Desirable Outcome/ Deliverable
1. Review and Evaluation of Data		
1.1 *Data Evaluation Method*	The mathematical or nonmathematical methods used to understand the nature and behavior of the data/ information to be used in the model.	A formal methodology, including descriptive statistics, plotting of data, and investigation of data quality, where applicable.
1.2 Search and Collection of Data	The methods to search and collect data and information.	Search for missing information, searching for extra data to validate the solution, searching for conceptual information that is missing from the learned material. Use of search materials, including the class notes, text book and online material.
1.3Determination of the Quality of Data	Deciding whether the size of the data to be used in the model is enough and data is of good quality.	Testing for the data reliability, where possible, obtaining different types, sources, samples of information. If not possible, stating the possible outcomes of low quality data, and statement of assumptions related to data quality.
2. Conceptual Modeling		
2.1 Making Assumptions	The simplifications and assumptions made to narrow down the complexity of real life density in the model.	Statement of all assumptions made in solving the problem and related to the data used. Sophistication in the assumptions by capturing real life concerns. A balance between assumptions made and the effort spent to model complexity. If additional tests can identify how realistic an assumption is, carrying them out.

Table 24 (Continued)

Category	**Definition**	**Desirable Outcome/ Deliverable**
2.2 Pictorial Representation.	Representation of the relationships within a system using visual tools, figures, schemas, outlines, etc.	Ability of representation of the systems using visual aids. (In the context of the current study, this task was not a requirement.)
3. Establishment of Performance Criteria		
3.1 Influence of Authority on Goal	Extent of coming up with the goal independently from a manipulation of an authority.	Understanding the main purpose of a model (and not perturbing it based on the request from the authority).
3.1 Goal setting	Understanding the goal of the exercise / purpose of the mathematical model to be developed.	Deriving a meaningful goal for development of the model, in line with what is in the minds of the client (or instructor).
4. Development of Conceptual Model and Potential Scenarios		
4.1 Mathematical Models Used	The type and complexity of mathematical model used in the overall engineering model.	The mathematical model developed should represent the knowledge and sophistication level of the student, as well as providing a clear path to obtain the established goal. The model should leave as few uncertainties as possible, and should take various aspects and constraints from real life.
4. 2 *Multiple Thinking Strategies*	Different type of models students can envision using for representing the system (even if they are not used).	The ability of multiple thinking is limited to students' domain knowledge. Therefore, at the senior level, students should be able to see and model the problem using different engineering backgrounds. Overall, the more thinking strategies, the better.
5. Modeling Calculations, Sensitivity Analysis, and Uncertainty Analysis		
5.1 Tools used to Carry out Calculational Models	Calculational tools including resources and software that were instrumental in reaching the ultimate model.	Students should be able to utilize a range of computational tools that are available, as well as carrying autonomy in ability to derive results without the tools.

Table 24 (Continued)

Category	Definition	Desirable Outcome/ Deliverable
5.3 Calculational Error Checks	Checking to make sure that the calculations are free of error / trembling hand error.	Students should ensure that their calculations are free of error, either by double checking the calculations by repeating them twice or by hand / computer calculations.
6. Results Evaluation		
6.1 What- if Analysis	Interpretation of results beyond the obvious, being able to take the results and interpret them under fictitious scenarios.	Models reports ideally should contain comments on what would happen if under extreme case scenarios. We note that this analysis does not have to be numerical, as in the case of sensitivity analysis.
6.2 Causal Explanations	Interpretations and explanations of why, as opposed to how the results are achieved.	Students should be able to correctly identify the sources of numerical results and make suggestions based interpreting them.
6.3 Ethical Interpretation	Interpretations of the numerical results based on the ethical considerations.	Students should be able to correctly identify the ethical consequences of their interpretations and suggestions, including estimating what would happen to the society, public, their company, environment, colleagues, etc.
7. Validation and Verification		
7.1 Validation and Verification	Ensuring that the right model is built and that it is built in the right way.	Students should ensure that the model is built in the right way by comparing it to other models, as well as providing face validity. Questioning whether the model serves the purpose ensures whether the right model is built.

7.2.2 Qualitative Analysis

Identifying the differences among modeling skills through a qualitative analysis of the overall strategies was obtained by (1) analyzing the team reports and (2) the open-ended interviews focusing on the students' choice of modeling tasks and the reasons for their choices. In addition, an analysis of the student MEA responses that identified certain solution paths is provided. In the following sections, we describe the qualitative analysis that was conducted.

7.2.2.1 Qualitative Analysis of the Strategies Used By Different Cohorts

The first analysis studied the various pathways student teams chose when solving their particular MEA. The literature in problem solving indicates that experts and novices use different strategies to solve problems (Chi, Feltovich, and Glaser, 1981). This implies that as students' expertise increases, one is likely to observe a change in the strategies used to solve a problem. Following the literature that focused on expert- novice differences, we also identify the differences in modeling strategies of the both groups.

As the solution reports were graded, the graders were able to track and decipher the various solution paths students used. Figure 19 and Figure 20 provide these solution paths for the Tire Reliability MEA and for the CNC Machine MEA. Paths of modeling approaches were created by finding the commonalities and listing them all together. Next, this list was narrowed down to five strategies of possible routes (depending on whether the solution was desirable/ undesirable and correct/incorrect), and they were ranked based on their correctness and desirability from the point of engineering learning.

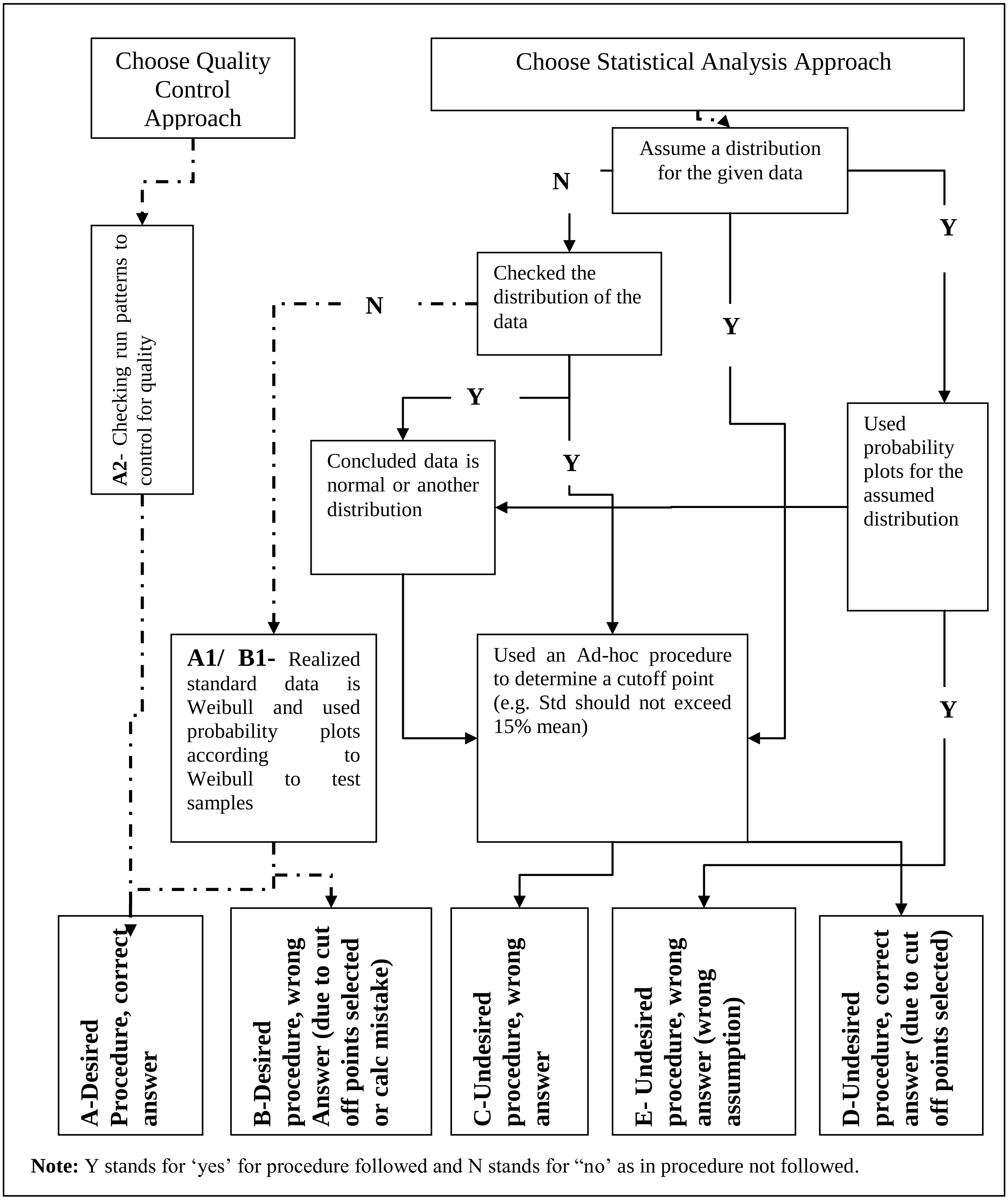

Figure 19. Approaches used to model Tire Reliability MEA

According to the figure, strategies are classified (along the bottom of the figure A through E) from the most to least desired in terms of how students approached the problem from a modeling perspective. The terms "correctness" is used to refer to whether or not students were able to identify the correct result. Each strategy is explained below.

A. ***Ideal solution:*** (desired procedure, correct answer) Students calculated descriptive statistics, tested the data for different types of distributions, noticed that the standard data is Weibull, used probability plots to test if other batches came from the same distribution, and determined that one batch passed the reliability requirements and the other did not.

B. ***Less ideal solution:*** (desired procedure, incorrect answer) Students in this group often used the procedure described in A; however, they made an improper calculation and were not able to arrive at the correct solution.

C. ***Acceptable solution:*** (desired procedure, incorrect answer) Students in this group often made an immediate and poor assumption that the data comes from a normal distribution. Even if rest of the procedure was correct, the result tends to be incorrect. However, when students state the assumption they make, we cannot conclude that they are entirely amiss in their solution approach, but rather that the student teams made a poor assumption.

D. ***Lucky solution:*** (undesired procedure, correct answer) Students utilized another approach, most often finding a cut-off point to determine the reliability (e.g., deciding that if 98% of the sample is within the limits, the batch will pass). As such, the students were fortunate in how they set these limits and arrived at the correct answer.

E. ***Poor solution:*** (undesired procedure, incorrect answer) Students either developed an ad-hoc method or used only descriptive statistics to arrive at their solution; and often these solutions were neither sophisticated nor desired.

An initial path analysis suggests that as the expertise of the student becomes greater, the students better utilize their domain knowledge, resulting in correct identification of the procedure in quantitative analysis of the students.

For the CNC Machine MEA, the following strategies are classified from the most to least desired in terms of how students approached the problem from a modeling perspective. Here the term “correctness” is used to refer to whether or not they were able to identify the correct result.

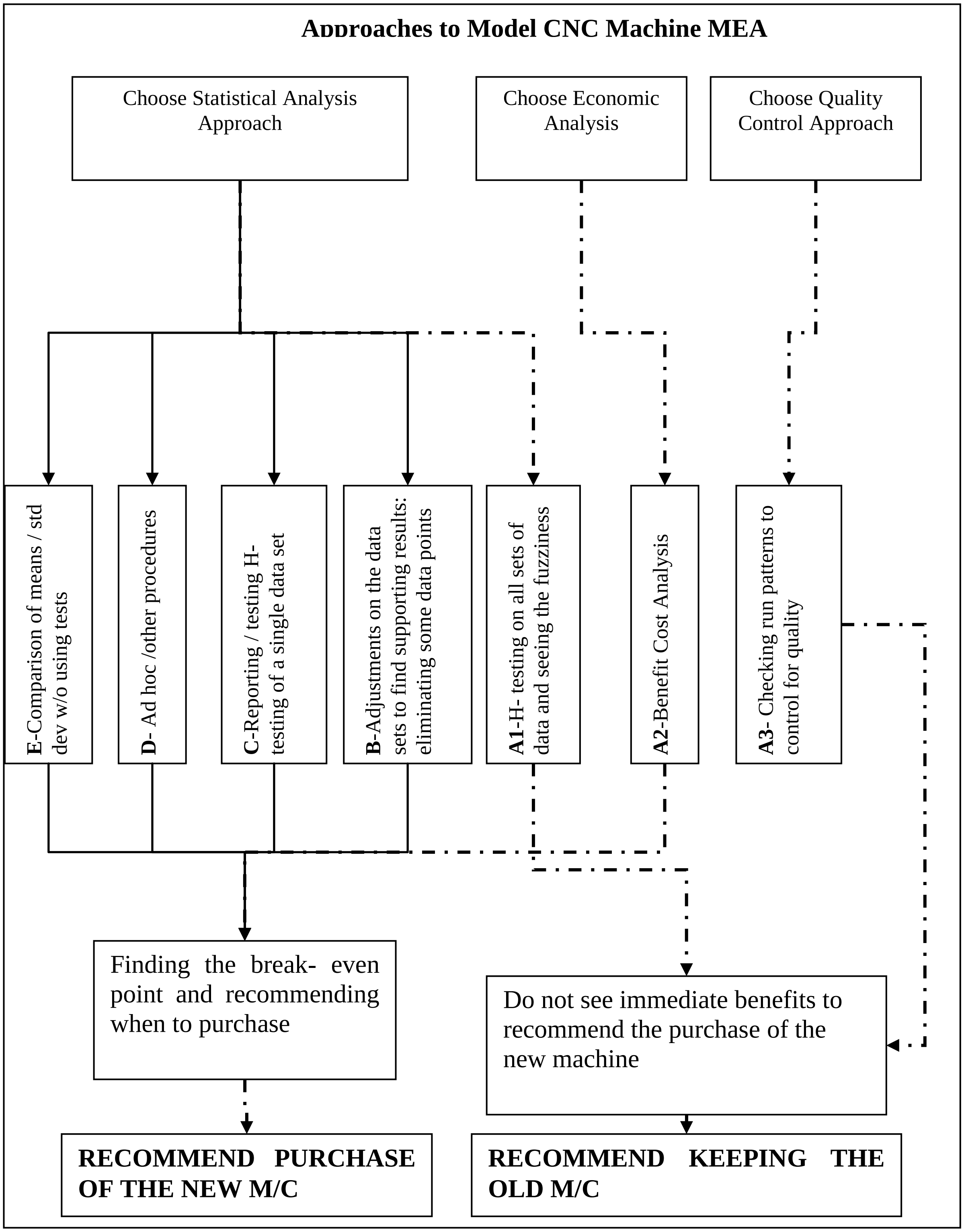

Figure 20. Approaches to model the CNC Machine MEA

A. ***Ideal solution:*** (desired procedure, correct answer) Students calculated ANOVAs/ t-tests for each type of data given to them, concluded that data gave conflicting results and decided not to recommend machine purchase; or students took an economic cost benefit analysis approach, determined a breakeven point for when to purchase the new machine; or took a quality control analysis approach and discovered that the machines did not operate within a desired quality level and recommended not to purchase the new machine.

B. ***Less ideal solution:*** (desired procedure, incorrect answer) Students in this group often used one of the procedures described in A; however, they made adjustments to the data set (e.g., removed outliers without assignable causes, etc.), and ended up recommending the purchase of the new machine.

C. ***Acceptable solution:*** (desired procedure, incorrect answer) Students in this group often assumed that since the memorandum was written in a manner that convince them to find a way to recommend purchasing the new machine. Hence, students tended to neglect a portion of the data and reported support information for purchasing the new machine.

D. ***Lucky solution:*** (undesired procedure, correct answer) For this group, students developed ad-hoc procedures other than those described in solution A ended up not recommending the purchase (i.e., creating certain limits on the number of products to accept a machine).

E. ***Poor solution:*** (undesired procedure, incorrect answer) Students either developed an ad-hoc method or used only descriptive statistics to arrive at a solution; and often these solutions were neither sophisticated nor desired. Students also recommended purchasing the machine, which is the incorrect response based on these procedures.

7.2.3 Qualitative Analysis of the Student Responses and Interviews

Based on the coding scheme provided in Table 24, Table 25 and Table 26 list the various trends emerging from the analysis of student solutions/reports and interviews. The tables classify which methodologies/approaches each cohort used for each MEA. We comment on each stage of modeling given in Figure 7.

7.2.3.1 Review and Evaluation of Data

The RED modeling stage focuses on how data collection and analysis will be integrated into a model. The tasks include: deciding on what kind of data/ information is required to build a model, determining how to collect the data, determining how to prioritize data, and when the data is available, deciding on the data quality and quantity. The search of data, as well as knowing where to search for data is also included in this category. The initial analysis included statistical tests to identify the characteristics of data, or tests to clarify the information other tasks.

Table 25. Overall procedure to model Tire MEA

Modeling Task	Modeling sub-step	Method Used	% carried out		
			Cohort I	Cohort II	Cohort III
Review and Analysis of Data					
	Visual / Graphical observation				
		Scatter plots	29	12	6
		Histograms	88	35	44
		Box-plots	24	12	0
	Numerical analysis of the data				
		Calculation of mean	88	100	100
		Calculation of standard deviation	76	100	100
		Calculation of other descriptive stats (skewness etc.)	18	12	0
Conceptual Modeling, Creation / checking assumptions and restrictions to simplify the real world problem					
	Checking data distribution				
		Probability plots	76	65	22
		Ryan Joiner Normality Test	0	29	22
		Chi-square goodness of fit test	0	82	33
	Creating assumptions related to data				
		Assumption of reliable data	41	24	67
		Assumption of Normality	35	11	56
	Assumption related to simplification of real life				
	Assumptions related to expected work from them				
Establishing the Performance Criteria/ Understanding the goal of the Problem					
	Recognition of problem goals and establishment criteria		100	100	100
	Recognition of ethical dilemmas		17.6	100	78
Mathematical Model- Comparison of data sets					
	Visual comparison				

Table 25 (Continued)

		Probability plots	76	65	22
		Eye-balling	12	24	44
	Numerical comparison				
		Hypothesis testing	18	88	44
		Confidence interval	0	35	33
		ANOVA	0	6	0
		Comparison of failure rates	53	24	44
		F-tests	0	24	22
		Quality control chart	0	6	33
Calculations and Uncertainty analysis					
	Calculations				
	Sensitivity analysis				
	Recognizing data uncertainty				
		Checking outliers	0	12	33
Results Evaluation & Reporting					
	Memo writing				
		Process description clarification focus	23	88	100
		Process justification focus	12	88	66
	Presentation		(N/A)	(N/A)	(N/A)
Validation/ Verification					
	Face validity		35	88	100
	External validity		0	18	100
	Verification		0	0	22

Table 26. Overall procedure to model CNC Machine Problem

Modeling Task	Modeling sub-step	Method Used	% carried out		
			Cohort I	Cohort II	Cohort III
Review and Analysis of Data					
	Visual / Graphical observation				
		Scatter plots	13	24	56
		Histograms	19	35	56
		Box-plots	0	6	0
	Numerical analysis of the data				
		Calculation of mean	100	100	100
		Calculation of standard deviation	100	100	100
		Calculation of other descriptive stats (skewness etc.)	6	6	0
	Checking data distribution				
		Probability plots	0	12	22
		Ryan Joiner Normality Test	0	0	22
		Chi-square goodness of fit test	0	0	0
Conceptual Modeling, Creation / checking assumptions and restrictions to simplify the real world problem					
	Creating assumptions related to data				
		Assumption of reliable data	47	29	100
		Assumption of Normality	88	88	89
	Assumption related to simplification of real life				
	Assumptions related to expected work from them				
Establishing the Performance Criteria/ Understanding the goal of the Problem					
	Recognition of problem goals and establishment criteria		100	100	100

Table 26 (Continued)

	Recognition of ethical dilemmas		30	94	89
Mathematical Method for Comparison of data sets					
	Visual comparison				
		Probability plots	0	12	22
		Eye-balling	0	30	100
	Numerical comparison	Hypothesis testing	82	88	66
		Confidence interval	71	88	66
		ANOVA	0	84	78
		Comparison of failure rates	12	24	33
		F-tests	0	0	11
		Quality control chart	0	0	22
Calculations and uncertainty analysis					
	Calculations				
	Sensitivity analysis				
	Recognizing data uncertainty				
		Checking outliers	6	12	22
Results Evaluation & Reporting					
	Memo writing				
		Process description clarification focus	47	83	100
		Process justification focus	59	88	78
	Presentation (N/A)				
Validation/ verification					
	Face validity		0	39	100
	External validity		0	0	67
	Verification		0	0	0

***Data Evaluation Method*.** A breakdown of the methodologies used by the students are provided in Table 25 and Table 26. Accordingly, as students become more experienced, there is a higher tendency to rely on numerical methods as opposed to the visual methods. For example, in Table 25 all cohort II and cohort III members use mean and standard deviation in identifying the characteristics of data (100% in each). The most important change taking place is the number of methods used to analyze data . We notice that as students become more practiced, they have a higher tendency to check for the descriptive statistics before modeling the problem, as well as using figures and drawings including probability plots, histograms or box plots to watch the behavior of data. This makes sense given that students are gaining more content knowledge and have practiced this content knowledge.

Search and Collection of Data. The MEAs assigned in this study did not involve data collection (i.e., data were provided as part of the problem), therefore, we do not speculate on the changes in data collection skills. Since the modeling tasks did not involve collection or search for data, we are not able to comment on how such skills develop over time.

However, through the interviews it was demonstrated that search for information at the senior level becomes increasingly more reliant on internet based sources (e.g., Wikipedia) as opposed to text books or class notes. This is a significant finding for many reasons. First, it potentially implies that students go beyond the resources on hand to obtain information, which is a self-regulated learning or potential lifelong learning behavior.

On the other hand, sophomores mention primarily consulting their class notes and textbooks. Of sophomore groups interviewed, six mentioned using their classroom notes; and of the senior groups, all but one mentioned using internet as the only a source for information. For example, a sophomore team mentioned that while solving the CNC Machine exercise:

> *"[...] textbook and notes were the two primary—probably the only sources. I don't think we really used the internet."*

Although the search tool was different, the content of the search was similar between seniors and sophomores, as both groups searched for reminders of what statistical tests to use (e.g., which test to use to compare means of two data sets), how to interpret results (what does it mean to have a p-value less than 0.1), how to use software to conduct tests, and occasionally looking up the definitions for concepts mentioned in the MEAs, such as 'reliability' and 'tolerance'.

Determination of the quality of data. When asked whether they found data sufficient to solve the MEA, students replied yes on all accounts; however, they also mentioned the need for additional samples or other types of information, particularly if they were in the situation in real life. All student teams suggested that the size (i.e., the number of samples) was sufficient for both examples, but would have preferred more samples for the CNC Machine MEA if the case were encountered in real life. For example, one of the sophomore teams suggested for the CNC Machine MEA:

"[..] if we were able to take our own sample, maybe we'd take a lot more data. It might cost more but you'd have more accurate results and you could actually see the viability of buying a new one [machine]."

As the CNC example suggests in Table 26, students accounted for the cost/ benefit ratio of collecting more data versus operating on the available data. Of groups interviewed, all treated the sample size in the Tire MEA (n=1000 data points) as sufficient and the sample sizes in the CNC Machine MEA (n=25) as small. When the students were asked whether they would require other types of information to come to a decision about the same problem in real life, the majority of the teams suggested that the type of data given in the CNC Machine MEA was appropriate; however, for the Tire MEA, they would need additional information. When the students were asked to further clarify the type of data they would need, they listed several types of information that are conveyed in other engineering courses apart from statistics. In the case of seniors, many recalled an exercise they were assigned two years prior (please see the SUV Rollover MEA, which can be obtained from www.modelsandmodeling.net).

This finding suggests that such problems, in this case MEAs, potentially have (a) long term learning and recall effects, and (b) impact on integrating concepts from different courses. This is referred to as the integrator role of MEAs (see Yildirim, Shuman, Besterfield-Sacre 2010b). Information most commonly referred to by sophomores and seniors are given in Table 27.

Table 27. Examples for extra information the students mentioned they would ask for

MEA	Information Asked	Related Course / Concepts or MEA
Tire MEA	Road conditions	SUV Rollover MEA
	Cost of testing / manufacturing the tire	Engineering economics SUV rollover MEA
	Details of customer complaints	
	How serious the tire wear is	Engineering ethics
CNC Machine	Lifetime of machine	Engineering economics
	The opinions of the operators to use the machines	Human Factors/ production
	Likelihood of machines to break down and maintenance	Production/ Operations research
	Expected rate of return on the investment and time scope of the machines	Engineering Economics
	Manufacturing quantity	Operations and Production

According to Table 27, evoking a modeling exercise in one course enabled the students to recall and make connections between multiple courses (i.e., statistics, engineering economics, production, operations research, engineering ethics), as well as previous modeling exercises. Overall, the data and information filtering ability of the students has developed to a desirable state. This category corresponds to Review and Evaluation of Data (RED) and was found to not be significant between to the sophomore and senior years, a desirable result from an engineering education perspective.

7.2.3.2 Development of Conceptual Model and Potential Scenarios

Conceptual modeling is possibly the most abstract and difficult part of modeling. The task requires seeing beyond the information provided, understanding the complexity of the real world, reducing and simplifying that complexity, as well as putting assumptions, limitations and boundaries on the model.

Making assumptions. Students' practice of assumption making was measured by investigating both the memorandum responses as well as the interviews. A major change taking place between sophomore and senior year is the type and number of assumptions. For example, at the sophomore year, first semester, when students were asked to list assumptions they made in modeling, they often listed ones that were secondary, or related to what the authority (in this case the instructor) has asked of them, such as assuming that the data provided is correct, or assuming that the story in the MEA is credible, etc. Student reports indicate that students made more sophisticated assumptions at the senior level. For example, some stated assuming that the data is normal to apply ANOVA, or that machines in the CNC MEA operate for 8 hours a day and produce a certain number of products in a year. Yet, most students created mathematical models without stating the assumptions in their reports. This implies that the reports of students do not fully reflect their thinking and knowledge level, and the interviews or verbal protocol discussions following the modeling tasks can reveal more information about the effectiveness of teaching. It is not uncommon for oral tests to be used in Europe at the college level and stated by some to be a more effective way of assessment than written tests.

In the interviews some students stated no assumptions when asked, despite, sometimes operating on certain assumptions while building their model. For example, some students decided to use an ANOVA in the CNC Machine MEA, implicitly assuming that the underlying distribution of data is normal. Similarly, to determine whether the batches were reliable, when students use probability plots, they implicitly assumed that the distribution of data sets should be the same. (Note, in this MEA it is possible, despite different distributions, that the data sets could still be reliable.) For example, one of the senior group members suggested that

> "*We checked normality before we assumed normality [...]. I think [I learned]a lot more looking at the assumptions for all the tests and making sure we weren't over-assuming or completely contradicting some of the assumptions before we started applying things [...]*".

Students expressed relative confidence in their solutions (70% to 97% confident), which may be desirable given that students had to make assumptions and were aware of the real life limitations. For example, suggesting that due to limited data, the results might not be 100% correct:

"We're confident [with our recommendations] given this data but if we were given more data we wouldn't be so sure. I don't even know how to answer that question [question of whether the student is confident in her answer] because we made a lot of assumptions."

Though not the general case, by the time students reach their senior year, several teams, although a minority, practiced checking assumptions related to their mathematical models before implementing them. Only four out of the senior groups followed the practice, whereas only one group in sophomore interviews reported having checked for the normality assumption before using the tests that require normality. Further, students were more comfortable in making assumptions at the senior level. A possible explanation is the increased level of knowledge in limiting conditions on models and the higher self-confidence in making assumptions. Table 28 provides a list of the assumptions that were stated by the students**.**

Table 28. Common assumptions listed and mentioned by the students

MEA	***Assumptions (Mentioned By)***	***Related engineering domain***
Tire MEA	Normality of data (Senior 3 teams/ Sophomore 2 teams)	Statistics
CNC Machine	Working days and hours (e.g. 8 hours per day and 250 work days) (Senior / 3 teams)	Production and Operations
	Normality of data (Senior 3 teams / Sophomore 2 teams)	Statistics
	Production volume of the machines (Senior- 7 teams)	Production and Operations
	Tooling costs (Senior – 6 teams)	Engineering economics
	Salvage value of machines (Senior- 4 teams / Sophomore- 5 teams)	Engineering Economics

According to Table 28, students made assumptions related to different domains of engineering. It is important to note that most of these assumptions were mentioned by the senior groups. Overall, there was a change in the quantity of assumptions stated, however, the assumptions related to the model and data for sophomores is more related to the assignment and expectations of the instructor, whereas seniors' assumptions were more specific to the construction of the model itself.

Pictorial Representation. Despite the fact that schematic resprentations are helpful in understanding the relationships among model parameters, the inputs and outputs to the system were mostly mathematical representations and numbers in the two MEAs. Therefore, it is possible that the students did not feel the need to create a pictorial representation of the model. No groups mentioned using pictorial representations. Students, however, did use figures like scatter plots, box plots, etc. to understand the behavior of the data (often generated by Minitab or Excel). Most groups answered the question of whether or not they used drawings with similar responses; the following quote provides an example.

> *"We used, the graphs we produced using the ANOVAs on Minitab, so after we'd put the data in and done the ANOVA—and we found—I think it was like four different graphs for each of the different things—and we compared the first machine to the second machine for all of those"*

Overall, findings related to conceptual modeling show that abstract thinking is relatively weak; but findings are supported by the literature on student reactions to complex phenomena. For instance, Resnick and Wilensky (1998) found that most people have a centralized mindset, preferring explanations with single causality. Similarly, Jacobson (2001) interviewed undergraduate students and found that students favored simple causality and predictability. It is likely that students in this study did not use multiple relationships in the models.

7.2.3.3 Establishment of Performance Criteria

Influence of the authority on goal. Influence of authority (in this study, the instructor) was observed from the interview transcripts. An important observation was made related to the influence of authority (ethical dilemma manipulation) on the purpose of model building, and its expected impact on the results. This influence was clear in the CNC Machine MEA. The MEA posed asked the students to develop a model that supports the purchase of the new machine. A student described his process for coming up with performance criteria as follows:

> *"I guess, conceptually, when I start, the first thing is – after reading the memo – is, "Okay, what are they exactly asking for? Like, what do they want? They want a model." Like, for this one, they wanted one. So like, that's where you have to start. Like, "Okay, we want a model." Then start, "How are we going to form the model?"*

Some students treated the question as a true real life experience, believing that the request of authority was not worthy of risking their "job security". For example, one senior team member stated:

> Member 1: "*I think at first we thought it [the result] was gonna be how are we gonna, you know, agree with our boss and say that we were for doing this machine and then I think we realized that there was so much evidence against agreeing with him that—and I think our main decision was how are we gonna disagree*."

Member 2: "*Yeah, I think we were like more—like should we try to manipulate the data or manipulate the results so that we're agreeing with our boss? Or should be just be straight up… [..] and be like…This is what the data shows and I don't know."*

This dialogue shows the students' interpretation of the goal and awareness of the ethical dilemma influenced by the write-up of the memorandum. This particular group chose not to manipulate the data, and stated in their memo that there is not enough information to suggest that the new machine is better. Despite the fact that students believe the results should support the purchase, they chose not to manipulate their results or the report; and hence, according to this argument some groups really treated the MEA case as an exercise for real-life (which is one of the intents behind the MEA construct). On the other hand, several sophomore groups implied that they thought they were manipulated by the directions given in the exercise, particularly when they addressed the MEAs in the first term sophomore year. Even as second term sophomores, cohort II students believed that their analysis should show that the new machine is better. For example, one team suggested in explaining their understanding of the goal:

"They wanted us to say the one was better or something, Vanguard was better."

Overall, even though the majority of the students correctly understood the purpose of the model, some students were influenced by the authority in the CNC Machine MEA, believing that the goal of the exercise was to demonstrate the new machine is better.

Establishment of Goal of Model. The majority of students were clear on what was asked of them except for the situations when they believed they were being manipulated by the authority. Overall there was no confusion on the goal of Tire Reliability MEA, and only minor confusion with the CNC Machine MEA; students thought that the goal was (a) finding a way to justify the purchase of the new machine, or (b) whether it is justifiable to buy the new machine. However, both these goals were equally reasonable to assume.

7.2.3.4 Construction of Calculational Models

Mathematical models used. Constructing a mathematical model that represents a system requires a person to construct relationships between concepts and principles about engineering phenomena and the interrelationships among different levels of the system. One of the most obvious changes in the practice of modeling between sophomores and seniors is the change in the methods a student uses to solve the problem.

The methods that students picked highly depends on their knowledge base. The first cohort mostly used probability plots in the Tire MEA and hypothesis testing with t-tests for the CNC Machine MEA, cohort II relied on chi-square tests for Tire MEA and ANOVA for the CNC Machine MEA. Cohort III (seniors) used a wider range of strategies, from quality control methods to engineering economics for the CNC Machine MEA. They also used failure rates for the Tire MEA, a concept that the sophomores had not yet studied.

Based on the change in the mathematical modeling, one could surmise that two types of conceptual change is taking place: (1) enrichment of an existing conceptual structure (i.e., the addition of new information to an existing theoretical framework) and (2) revision (i.e., acquisition of learning that is inconsistent with existing beliefs or presuppositions).

Multiple thinking strategies. When asked about the different strategies students used to model the problem, more and different types of strategies were mentioned by seniors. When asked how the problem would be solved, sophomore responses ranged from suggesting that they could not think of additional methods other than the one they used, to one or two additional statistical methods. We did not observe sophomores suggesting alternative methods from other areas (e.g., engineering economy) to model the problem.At the senior level, though, there were often three to four major areas of industrial engineering used to approach the problem. The conceptual knowledge from statistics, production, quality control and engineering economy were all mentioned in the interviews.

7.2.3.5 Calculations, Sensitivity and Uncertainty Analysis

Tools to carry out calculational models. There is a clear shift in the ways students carry out calculational models from the sophomore to senior year. Students are limited in their sophomore year to carrying out calculations by hand due to lack of software knowledge. This hand calculation practice completely switches to statistical packages (in this case Minitab), such that by the time they are seniors, more general software packages are used, like Excel. At the senior level students' use of hand calculations was limited. A potential indirect implication of the use of software is that the models built are limited to the type of software packages used. In a few instances, where students decided to test different methods, they stated they changed their minds when they could not figure out how to implement it on the particular software package. Students also expressed feeling more comfort during their second term sophomore year than their first term for several reasons. One reason was that statistical software was introduced, as opposed to having to use hand calculations or a single limited program:

> *"[We are] more confident that we actually got a right answer rather than just handing in something. We used to just plug stuff into Excel because that's all we knew how to use. So I think learning how to use, like – The Minitab – and all the other software, helps us, like, expand on it."*

Changes in sensitivity analysis**.** Sensitivity analysis as a concept did not appear to be a regular practice for neither seniors nor sophomores. As one potential example, a senior group changed the tolerance limits in the CNC Machine MEA:

> *"[...] we widened the tolerance a little bit just to see how sensitive they were to the tolerance. They were increased a little bit."*

Another group checked the robustness of their model comparing the results with and without the suspected outlier points:

"[…] *we left it [outlier point] in to start with."* "*It [Its change in results without the outlier] was negligible. It wasn't a very significant change."*

There was also a contrast in checking for outliers between the sophomores and the seniors. In fact, sophomores, in general, did not check for outliers. The following dialogue related to the Tire MEA respresents how sophomores generally ignored checking outliers, indicating that in large sample sizes the impact of outliers would not be strong.

Interviewer: *"Did you check for the outliers?"*

Student Team: *"We knew that there were probably some especially the 25K but we didn't know if that was just pertinent to the data.[…] since it was 1000 points we thought it wasn't going to affect it all that much."*

In the CNC Machine MEA, sophomore teams who believed the results of their analysis should support the purchase of the new machine mentioned "playing around" with the data:

"[We played around with data] A lot. […] If our boss is telling us to do something, we're trying to find things to support that."

Students also felt the need, when the results did not make sense, to conduct some type of sensitivity analysis. For example, a sophomore team struggling in using confidence intervals with the Tire MEA mentioned;

> *"We did that [playing with data] when we were struggling with the confidence intervals [...] we changed it to like 5% confidence, and then it still wasn't working, and it would just like – it was still between 4 miles. And then the ranges of the miles to failure or whatever were much greater than that, so very few fit into this confidence interval."*

Changes in the calculational error checking. Checking for calculational errors appeared to be one area where the students deteriorated over the course of their undergraduate education, possibly resulting from the reliance on software packages. Particularly, when using more structured statistical packages like Minitab, the students conducted less error checking compared to students who used semi-structured packages like Excel where the student enters or chooses a formula or conducted calculations by hand. However, calculational errors decreased when the students switched from hand calculations to the software packages. In fact, the following standard phrase was often repeated:

> *"We trusted Minitab".*

Interestingly, some students checked their calculations by hand when they were not confident with the software package, as one team suggested:

"We checked one or two [calculations], cause we weren't sure if we were doing it right in Minitab, but…I think that was really it."

"We kinda as we went along [the calculations] made sure they made sense with what was there and what we knew was supposed to happen. But after the graphs were done, we didn't revisit it […] we were just like "eh.""

7.2.3.6 Results Evaluation.

What- if Analysis of Alternate Scenarios. In the interviews, the students were asked to evaluate what-if type of questions. For example, they were asked how they would react if their recommendations in the reports were incorrect. Further, students were asked to consider situations where their recommendations might differ from those in their memorandums. In particular, we asked students if they were faced with the same problem in real life, would they consider doing something additional. Many student teams mentioned collecting more data. Student responses to these questions ranged from the naïve to sophisticated considerations. The following dialogue with a sophomore team provides an example for a sophisticated answer.

Interviewer: *"If you wanted to come up with a similar decision [whether the tire batch is reliable or not] in real life, what other information would you consider?"*

Member 1: *"Um, probably like where the tires are like, I don't know, like the area that they're being driven on. Weather conditions, road conditions, because obviously a tire wouldn't be as reliable if they were like traveling up like a cliff as opposed to like a highway."*

Member 2: *"Material of the tire."*

Member 1: *"I mean if it's, obviously it's rubber for the most part, but if they like were designed in a different way, like the shape and the actual tread. If it's like different from their other brands or models or something... "*

Member 3: *"Maybe like costs especially. How long it takes to make and how much you have to pay for the labor."*

Students suggested that their solutions might have been better in real life, the major reason being MEAs are graded; and hence, they are not true reflections of real life:

"I mean, technically it was just an assignment in class and only is worth very little bit of your grade and everything".

Causal Explanations. Perkins and Grotzer (2000) found that students tended towards simple causal explanations of complex phenomena, missing the links within a system, as well as complex causal relationships. One reason for this is that learners tended to focus on the structure of systems rather than on the underlying function. As a result of feeling more comfortable in using mathematical models, the students felt more comfortable in interpreting the results as well. Comparing their own methodology from fall and spring sophomore semesters, one team suggested:

> *"I think it [results] definitely fit better this semester after knowing how to do the ANOVAs, and… I know when we worked on it last semester with our other team member we were all kind of confused as to what exactly we were supposed to do… t-tests weren't really so straight forward at that point, like we were kind of, like I think it fit better—I think it fit a lot better now in this semester."*

***Ethical interpretation*.** In the posed modeling questions, it was intended that students realize and reason ethical implications of the MEA. For the Tire problem, the ethical issue was possible damage to the end-use customers; and the CNC Machine MEA, the ethical issue was the boss' insistence on finding results that favors the purchase of the new machine.

When asked about the ethical consequences of their decisions, the majority of students decided they would do what is in the best interest to the public. However, when the decision had no direct risk to human life, ethical issues were more likely to be overlooked or given less weight. An example conversation from the CNC Machine shows the following:

Interviewer: ***"****If you made the decision to purchase the new machine, and it turned out it actually was not a good idea. So what do you think would happen?"*

Member 1: *"Okay, you'd get in big trouble. Well, your boss told you to do it."*

Member 2: ***"****Back and forth. And also I feel like purchasing one machine is not gonna be the end of the world—it's a first thing—I mean, yeah, it's important, but it was replacing one machine and it's a factory and they have all these different things—we're not replacing all their CNC machines and they have 80 of them—it's deciding whether to buy a new machine or not. It depends how much the difference was and bad or how drastic it was, but—it wouldn't be good, but."*

Member 3: *"I feel like if they found out that you purposely skewed the data, that you would get in trouble, but if they were just like "Oh, we probably should've gone with the other machine" and, you know, "You didn't do so good—try better next time." But if they found out like "Hey, I know you messed with this data, or you didn't report it correctly," then you'd be in trouble."*

Member 2: *I don't think I'd be able to just do it. The bad thing is though if you got away with it once, you'd do it again. I just couldn't do it. My conscience would kill me. I wouldn't do it. Yeah, my conscience would just kill me."*

According to the memorandums and interviews, we observed that recognition of ethical issues was obtained with esposure to discussions of ethical discussions given throughout the engineering program. This finding clearly emphasizes the benefits of integrating ethics education into engineering education. Even though the majority of the groups interviewed did not have a formal ethics education, they had been exposed to ethical responsibilities of engineers throughout their engineering program, either through discussions in the class, multiple seminar talks, or similar MEA exercises in other courses; and it was noted that the ability to recognize and reason out ethical dilemmas was better for the senior level students.

7.2.3.7 Validity and Verification

From the interviews, it was evident that students implicity used face validity. Students, for example, used figures and summary statistics such as mean and variance to obtain an overall conception about the solution. They recognized unsystematic approaches to analyzing data from multiple ways, such as repeating the solution approach, or eyeballing the results to see if they made sense. Students suggested that they got a 'feeling' for the result, and they tried to justify that feeling. A group member from cohort II suggested that while solving the Tire Reliability MEA:

> *"We've done it a couple of times, just like, see if we're on the right track if we're not sure we're doing the right process. I think it's easier to choose if you know what they're asking for and we have a set amount of tools that we're able to use after learning this class, we can apply what we know and see if it'll work…."*

7.3 SUMMARY OF STUDY 4

In this study, we have reported on the comparisons of strategies for modeling and changes between seniors and sophomores that are observed in the interviews in a descriptive manner. According to this analysis, the effect of domain knowledge on modeling was not found to be as straightforward as expected. In fact, the results suggest that seniors, when given a problem that can be solved in multiple ways, actually do present the awareness that multiple methods could be used to solve the problem. However, this does not necessarily translate to a higher quality solution. It was generally found that seniors provided a less complicated solution method by providing sufficient assumptions.

This study presented seven aspects of modeling and the potential changes that take place between sophomore and senior years. The use of MEAs followed an analysis of the memorandum reports and interviews from several aspects of modeling. Though not exhaustive to all aspects of modeling and educational programs, contexts analyzed were common to majority of the engineering disciplines.

Findings indicate that it is important to encourage the modeling process by providing modeling experiences to students early in their undergraduate program. Models built evolved over time; and providing such exercises helps to put engineering practice in context.

Though the analysis presented here is not sufficient to explain and predict behavioral changes of all students, it does contribute to the understanding of how students think about modeling. Indeed it suggests that students, by and large, are able to improve and replace their modeling thinking and approaches. Further, students are aware that knowledge acquired is subject to change.

This analysis also discussed changes in students' modeling abilities. First, seniors were able to provide solutions that were more generalizable than the sophomores; and they used mixed methods, such as combining statistics with economic analysis, etc. Further, experience was a contributing factor. Students indicated that both their experience in class as well as out of class helped them to develop their solutions. Seniors generally agreed that their co-op or internship experiences increased their level of realization of how certain methods could be used. However, they also indicated that classroom exercises were helpful.

Seniors in particular were able to make use of previous ethical reasoning experiences in resolving their decisions. For example, a previous MEA given to the seniors in their sophomore year had provided them with a benchmark on how the lives of people could be affected by unreliable products. Students recalled this experience and their reasoning from this experience to understand the overall impact of their suggestions on the new MEA.

Another issue that we probed was the students' attitude towards MEAs. Overall; students expressed a positive attitude change from first term to second term sophomore year. For example a sophomore student suggested:

> *"I like them [MEAs] better. I think we dreaded them like first semester of this year, and then like, we've gotten better, so, and we do well on them, so it makes us feel better about them."*

Students liked the modeling practice more as they became better at it. Overall, the students were able to suggest that the education they received in the classroom may be improved further by adding more real life experiences. Students felt that they were given the theoretical background, but often the applicability of these methods or the reasoning (as to why and how engineers use these methods) was neglected, indicating that it is often not until their co-op rotations that they were able to see the applications of what they learned in the classroom. One student, in particular, referred to his manufacturing co-op experience where he had seen similar problems of quality and reliability and he knew how important it was to a company.

8.0 DISCUSSION, FUTURE WORK AND SUGGESTIONS

8.1 OVERALL SUMMARY

In this dissertation, the impact of three cognitive factors on development of engineering students' modeling skills has been analyzed. These three factors were self-efficacy, metacognition and epistemology. To the best of our knowledge, the studies described here are the first to develop and test the impacts of these factors on modeling, using responses of students from sophomore and senior levels in engineering education. Although ABET does not specifically list modeling as a targeted outcome of engineering education, many of the eleven outcomes have a direct link to engineering modeling. Thus, from a practical as well as an intellectual level, findings of this dissertation could improve students' ability to model by implementing pedagogical practices aimed at improving students' self-efficacy, epistemology and metacognition. The specific achievements of each study of the dissertation are summarized in the given figure.

Contribution	Specific Titles of Contribution to Engineering Education Field
Study 1: Self-Efficacy Scale Construction & Measurement of Impact of Self-Efficacy on Modeling	• Developed EMSS • Conducted factor analysis and laid out the factors of modeling self-efficacy • Analyzed differences between the modeling self-efficacy levels of different years and disciplines of engineering • Laid out the sources of building self-efficacy and how MEAs can be instrumental in development of self-efficacy • Developed a theoretical framework of how modeling self-efficacy influences growth of modeling skills through testing of main effects and moderation • Provided a testing on the validation of EMSS including nomological and discriminant validity
Study 2: Measurement of Impact of Epistemology on Modeling	• Built a framework between epistemic beliefs and their expected impact on modeling growth • Developed a theoretical framework of how epistemology influences growth of modeling skills through testing of main effects and moderation
Study 3: Measurement of Impact of Metacognition on Modeling	• Listed metacognitive properties of working on MEA type tasks • Developed a theoretical framework of how metacognition influences growth of modeling skills through testing of main effects and moderation
Study 4: Qualitative Analysis of Change in Modeling Skills	• Provided a summary of detail changes observed from student reports and interviews in a descriptive manner, using examples from student responses • Analyzed and broke down the specific methodologies and paths used by students in modeling the MEAs

Figure 21. Summary of dissertation sections

In the first study of the dissertation, under the self-efficacy chapter, a novel engineering modeling self-efficacy instrument titled the Engineering Modeling Self-efficacy Scale (EMSS) is created. Testing of this instrument was conducted on a broader engineering group including students from civil and industrial engineering disciplines. The overall scale was created based on a comparison with other scales from the literature. An analysis of the factor structure revealed that there were seven underlying dimensions of modeling self-efficacy, which are well suited to match the stages of self-efficacy laid out by Tsang (1991). The EMSS was tested on data collected from industrial and civil engineering students at both the sophomore and senior levels. Results suggested differences between sophomores and seniors in particular for three dimensions of modeling self-efficacy (i.e., Process Modeling, Interpretation, and Uncertainty and Validation). Female students and sophomores reported lower levels of self-efficacy overall. Following this analysis, the impact of self-efficacy on modeling skill growth was tested. Results indicated that self-efficacy has a substantial explanatory power in a modeling ability development.

In the second dissertation study, testing was carried out on how epistemic beliefs influence modeling. Results demonstrated that the students are negatively influenced by the naïve ways of thinking in simple knowledge, certain knowledge, innate ability and quick learning dimensions. Innate ability influenced five out of seven dimensions for the sophomores and seniors. Certainty of knowledge influenced the review and evaluation of data. Omniscient authority was not a significant factor.

In the third dissertation study, the impact of metacognition on modeling skill growth was tested. MEAs were demonstrated to show metacognitive properties for engaging students to: (1) think about formulating a model to solve a problem, (2) explain their modeling strategy to group members, and (3) write about their model. Sharing their experience with group members, or observing that a method does not work as intended, students can also correct their misconceptions and incorrect knowledge. The testing conducted on sophomores suggested that students who show higher metacognitive abilities are better or faster in developing modeling skills, as measured by their MEA rubric scores. Student who scored higher on self-checking, planning and cognitive strategy scored higher on their modeling ability over the course of two semesters, compared to students with lower skills. In particular, students with higher scores on planning and cognitive strategy had a more upward sloping growth trajectory, implying that it took them less time to gain modeling ability of a desired level or they had higher scores after the same time period, compared to their lower metacognition level counterparts. At the senior level these findings were repeated to a large extent. In particular, self-checking and planning retained their significant positive main effect, and cognitive strategy has a strong significant effect for the senior students. Awareness, in both levels, did not result in a significant impact.

Despite the relatively small sample size and short time frame, in these three studies, particularly for the sophomore students, we were able to demonstrate that all three factors - self-efficacy, metacognition, and epistemology - have significant impact. The dissertation thus informs the discussion in engineering education about the impact of students' cognitive backgrounds on their success. Similar to other quantitative disciplines, it is important to understand the behavioral aspects of engineering; indeed, this is one of the earlier studies taking that initiative in engineering modeling. When the significance of the results is tested using a

Bonferroni correction, we still find significant contribution and meaningful results, which is important given that we are simultaneously testing multiple hypotheses on related constructs. The results of this work provide promise that future research might capture additional effects of cognitive backgrounds on modeling, if a larger sample and a longer time framework is taken into account.

8.2 A THEORY OF CHANGE IN MODELING

Based on the findings of the four studies described in the dissertation, the following propositions can be made for the growth of modeling skills in undergraduate education. The list of propositions relating to modeling is given in Table 29. These propositions can be considered as a call for action to understand and test the impact of each on various educational environments.

Proposition 1. *Modeling development is achieved as a function of the system analyzed, the domain knowledge of reference, and the interpretations that students are able to make from the modeling exercise based on their own cognitive, social and motivational limitations.*

Table 29. Summary of Propositions Relating to Modeling

Proposition 1	*Modeling development is achieved as a function of* the *system analyzed, the domain knowledge of reference, and the interpretations that students are able to make from the modeling exercise; based on their own cognitive, social and motivational limitations.*
Proposition 2	*Making the model parts discrete is useful for idea generation.*
Proposition 3	*Requirement of skills from various different domains of engineering, different points of seeing the modeling problem, and transformation of one domain to another help in development of modeling.*
Proposition 4	*Modeling exercises as a way of introducing a new but highly domain related concept does not work well in formalization of new knowledge.*
Proposition 5	*No single theory explains the idea generation process in development of a mathematical model. It develops based on students' knowledge, experiences, perceptions, analogies, and without considering the student's history, interpretation of their development in mathematical models does not make sense.*
Proposition 6	*Modeling exercises help students grasp the complexity of real life, within a frame.*
Proposition 7	*Modeling exercises have benefits in developing social skills of students, including the ability to communicate, write and work in teams.*

In order to achieve this balance, an educator should focused on understanding the students' background and ideas related to science, their degree of understanding of engineering concepts, as well as how well the students can associate with the problem or system under study given their current knowledge base. A more relatable system may achieve higher educational benefits than an alternative that is less relevant or interesting. The clarity of the instructor, as suggested by students, was an important factor. Reflecting on why they were not as successful as they could have been, students often blamed the instructor's teaching ability; and as to why they learned better, students also commonly stated the instructor.

Proposition 2. *Making the model parts discrete is useful for idea generation.*

Students' level of abstraction was not found to be sophisticated. The idea of making something discrete is a useful practice to help select general ideas that are consistent with the real problem, such as the part of the model and quantities of the parts of the model. The relationships between the parts of the model, and how they are conserved within the system, are key aspects of the model.

Proposition 3. *Skills from various domains of engineering, different perspectives for modeling the problem, and transformations from one domain to another all contribute to the development of modeling.*

The idea of interpreting data and findings by pulling together various backgrounds helps to develop a powerful educational model (Gobert and Buckley, 2000). In the more difficult MEA (Tire), students' concept of reliability was enhanced from their interpretation of statistics, engineering economics, and quality assurance.

Proposition 4. *As a way of introducing and formalizing new but highly domain related concepts, MEAs do not work well.*

MEAs introduced throughout this study allowed the students understand the relationships between what is learned in the classroom and actual engineering practice taking place, as well as recognize similarities and differences to approaches to solve the problem. With that said, MEAs were not helpful in introducing new concepts. For example, students showed low interest in understanding what reliability / tolerance implies, as measured by their searching (both online and in their texts) for new information.

MEA exercises can be described as a means for students to put into practice their classroom knowledge, discuss and think about how to use their knowledge with respect to classroom goals. From this perspective, MEAs help to integrate and reinforce information, rather than help to discover new concepts.

Proposition 5. *No single theory explains the idea generation process in development of a mathematical model. It develops based on students' knowledge, experiences, perceptions, analogies; and consideration of this background is necessary to interpret students' development in mathematical models.*

The generation of a mathematical model and interpretation of the results of the model were initiated by students' experience with previous similar problems, real life experiences, the analogies made from other models, and the way they perceived the information given to them. Students, based on their previous experience with a particular MEA could decide to use a similar mathematical model. For example, some sophomore students decided to use hypothesis testing for the CNC machine MEA in both semesters. On the other hand, the student's experience with hypothesis testing in the first semester partially determines whether they kept the same model or not in the second semester. A group of students who felt that they did not understand the MEA the first time opted to use ANOVA the second semester.

Proposition 6. *Within a framework, modeling exercises help students grasp the complexity of real life.*

An MEA's function in understanding the complexity in real life is significant. Students' ability to link their statistical results to economic and operational constraints in an engineering environment is important and provides a quick start to their engineering career. Yet, interviews also showed that while working on these problems students kept in mind that it was a class assignment. Sophomores kept time limitations as a constraint in their mind, often stating that they wanted to spend minimal time on the exercise as possible; seniors indicated that a "good enough" answer was acceptable. Thus, even though students considered the extra complexity of the problem, classroom constraints (or experimental study constraints in the case of seniors) limited in their motivation.

This proposition may be linked to: (1) students' motivation to learn on their own, or self-regulated learning, and (2) lifelong learning practices. Students created limited relationships between their day-to-day learning goals (e.g., understand the concept of ANOVA) and overall learning goals from engineering (e.g., be able to use ANOVA as a professional engineer in their career). This finding may provide a future engineering education research goal - improving students' self-regulated learning strategies.

Proposition 7. *Modeling exercises have benefits in developing the social skills of students, including the ability to communicate, write and work in teams.*

The modeling practice, and in particular the MEAs, goes beyond the general exercises used in the classroom. The documenting and teamwork aspects of the practice help students to learn to integrate their ideas and solution to arrive at the best possible model. Students are forced to think more collectively than individually while working on the problems. The development of a model, as well as changes in conceptualization and calculations being performed are discussed before implementation, thus helping students' discourse skills as well.

8.3 LIMITATIONS AND FUTURE WORK

There are several limitations to this overall study. Because the dissertation does not control for the effects of university or engineering discipline, it cannot investigate potential differences among institutions and disciplines. Consequently, it must be left to future research work to determine, for example, whether substantial differences in engineering modeling self-efficacy, metacognition and epistemic beliefs exist between different schools or engineering programs of students and if these differences can equally reflect on the development of modeling abilities.

In developing our initial research model, we drew heavily on theory and educational research. Researchers following up on this study may want to compare the theories in areas where they lead to different predictions. Even though self-efficacy theory offers significant promise for modeling research, future researchers might consider complementary theories that may also be relevant in modeling context. Also, we relied on student reports collected within a class and the survey instruments conducted via online systems. As a consequence of using self-reported data it is possible that some common response bias across constructs was introduced. This may partially explain the significant relationships observed between cognitive constructs and the various outcomes studied. Future research might replicate the testing using measurements that do not depend on self-reports.

For the EMSS instrument, although our analysis suggests that certain items should be discarded, it is possible that for other engineering disciplines in which this instrument may be used those items do matter. It is recommended that researchers who utilize this scale employ all 36 items and perform a confirmatory factor analysis. Our sample includes students from a single institution and two disciplines, and thereby might not represent the characteristics of student from other institutions and other engineering disciplines.

From a pedagogic point of view, more future research is required to understand the role of the instructor on students' views on modeling. This aspect could be useful in realization of why some students model engineering systems differently than others. In the future extensions of this study, we intend to include other cognitive skills and background factors that might play a role in how students model.

The findings ultimately need to be replicated by future work across other settings and over time before they can be fully accepted. Future studies should aim to develop scales for engineering modeling, and should test for differences in measurements with the various available instruments on different engineering populations. Our analysis included a year of data collection. If possible, future research should extend the time period of the data collection. Additionally, other instruments can be tested to measure the constructs of self-efficacy, metacognition and epistemic beliefs to increase robustness of the findings.

It is also interesting to study the retention of students in engineering careers and how the students' backgrounds potentially influence this retention rate. For example, how do students' epistemic beliefs influence their career choice is an interesting question that waits to be answered. Such a study would require a longer term longitudinal experiment of the cognitive backgrounds as well as a follow up on the career choices after graduation, which is beyond the scope of this dissertation.

In addition, future work could address a study where the three constructs are tested together for their impact. It is possible for one or more constructs to mediate or moderate the relationship between another construct and modeling skill growth. Again, such a study would require a larger sample size due to the increasing number of variables tested, but is likely to contribute to the understanding of the relationship between modeling and the cognitive background of students.

A distinct challenge in this study was the collection of data and the time of data collection. In particular, to measure the backgrounds, we had a single time point in the growth curve models. Future work should try to address measurement of cognitive background on multiple time points, and if possible, as many times as the modeling outcome measurement.

The results of the current study can be used to assist in creation of tests to identify students who are better suited to becoming engineers and modelers. Modeling skills could be incorporated into an assessment tool that could then be used to identify high school students with high levels of self-efficacy in modeling, who may be better suited to study engineering. By selecting and accepting these students who score highly on the self-efficacy instrument, engineering schools might improve their longer-term educational success.

Most importantly, to improve self-efficacy, metacognitive abilities, and epistemology, specific MEAs can be designed to include additional activities requiring cooperation and pooling of ideas such as general discussions on activities, comparisons between approaches to modeling before or after the exercise. This action may help to develop the students' understanding of how engineering modeling is also a social process.

8.4 SUGGESTIONS FOR PRACTITIONERS

Educating students so that they achieve higher modeling abilities will benefit educational institutions. How might engineering faculty use the developed scale and information given in this dissertation? First, studies make it clear that independent of the amount of education and experience a student receives, their learning or academic performance can be hindered by low self-efficacy, metacognition and naïve epistemic beliefs. Hence, despite instruction, faculty may not be able to change the modeling abilities of a student within a course or a semester period. Realizing this constraint, practitioners can viably set their outcome expectations. An instructor's effort in teaching might not be fully reflected in the student's ultimate course grade, due to the cognitive barriers. Further, institutions should consider the backgrounds of students in evaluating the performance of teachers. To do this, it may be necessary to create systems that evaluate the motivational and cognitive systems of students which can then be feed into educational curriculums and teaching evaluations.

In initiating dialogue with students about modeling, an instructor may benefit by shifting the students' attention from the outcome to the process of model development. Thinking about their process builds a metacognitive improvement role. Engineering educators can focus on the fact that the inputs and outputs of a system and the relationship between them are subject to one's abstraction and interpretation, coupled to their knowledge base.

Addressing the importance of abstract and vague information (i.e., external conditions of the model that are not obvious from reading the MEA) in determining the results and their impact on the results, can help students to create connections between the model they created in the classroom and potential future models they may build as professional engineers.

A result from this dissertation is that self-efficacy in engineering modeling is not well developed as students move from the sophomore to the senior level. Attempts to increase the modeling experience through the use of MEAs (e.g., having students with demonstrated modeling abilities as mentors to novice student modelers, and training them to be 'role models' for modeling) may be a way to reduce low self-efficacy. Further, faculty can focus developing self-efficacy in their courses, by providing further practice for modeling, giving verbal encouragement to help increase the level of self-efficacy, as well as enabling students to observe successful modeling outcomes of their peers. Reducing math anxiety levels also can be beneficial by leading to increased modeling self-efficacy, which in turn increases modeling outcomes.

For students with naïve epistemic beliefs, educators can adapt instruction to guide those into higher level thinking; and adapt instruction for low scoring students to assist their growth. Traditional teaching roles are transitioning from transmitting knowledge to facilitating learning (Brookfield ad Preskill 1999, Sarasin 1999, Goodlad 1992). A basis for this idea is presented by Knowles (1980), who defines andragogy compared to pedagogy. Andragogy encourages students to be more autonomous, assessing their own capacities and needs, and accepting responsibility for their own and others' actions. MEAs can support andragogy practice by allowing students to become more autonomous, determining through their own actions how to best model and solve the posed MEA problem, as well as accept team-based responsibilities. Therefore, as MEAs become more common in engineering, classrooms can become less hierarchical environments. As modeling tasks are conducted in teams, the role of an instructor involves more than just delivering course content, but rather requires for helping the students in their inquiry of abstracting the real world. This should not give the impression that teaching is de-valued when MEAs are implemented. As Mayer (2004) suggests, unguided discovery methods can only be attained if they are supported by trained facilitation. Implementation of MEAs should provide a metacognitive practice, helping students to better reflect on their thinking, modeling process, as well as use of cognitive strategies and planning. To summarize the points made, we provide a list of ten important things that practitioners can do to improve learning to model in their classroom:

1. Give information to students about their own backgrounds. Students are often unconscious of the epistemic beliefs and metacognitive habits they have or will form, as well as their level of self-efficacy. Helping the students to realize their weaknesses in cognitive backgrounds and the possible effects can help to minimize possible negative effects.

2. *Pay attention to how student teams are constructed.* Constructing student teams in a balanced manner, whereby students can learn from each other and thus increase each other's self-efficacy through role modeling, can contribute to learning to model.

3. Encourage students. When an instructor feels that a student is not reflecting her full ability, encouraging the student that she can do better can help to repair low self-efficacy, which, in turn, will result in higher modeling learning.

4. Make modeling exercises relevant, and gradually increase their difficulty. When increasing the self-efficacy level of a student, it is important that the modeling tasks assigned match their capability, as well as their knowledge. Introducing tasks that match their capabilities and then gradually increasing the difficulty is likely to result in higher self-efficacy, helping them to learn to model.

5. Ask for a plan / sketch of solution. To improve metacognitive thinking, the students can be asked to produce a sketch and a plan of their model prior to diving into their solution. This precursor step can help students' thinking to clarify the method to be implemented.

6. Ask for multiple ways to approach a problem. Often instructors ask students to provide a single solution for a model; however, in real life it is not uncommon that an engineer is expected to exhaust all possible options to come up with alternatives. Therefore, encouraging students to think and report a number of different ways can help to build metacognition through cognitive strategy.

7. Use reflective statements. Metacognitive abilities of students can be improved by implementation of reflective statements over the course of a project. Carrying out reflections during and after the modeling exercise can help students master the planning and self-checking dimensions of metacognition.

8. Give information on scientific thinking. Providing the students with more sophisticated epistemic beliefs and scientific thinking is important to challenge naïve epistemologies, which can contribute to learning to model.

9. Give more real-life experiences. We observed that students often think in terms of short term goals, such as getting an A or graduating, rather than preparing for the long term goal of being a successful engineer. By providing real-life modeling experiences, students are more prepared and hopefully motivated to feel and act like engineers. Therefore, giving modeling exercises, in particular, MEA-like real-life based exercises, contributes to this thinking.

10. Expect more and communicate it. Similar to the previous recommendation, expecting that students prepare their answers as if they were actually working as engineers and making this expectation clear can help to sever the naïve student thinking, such as 'it is just a class' or 'it only contributes so little to my grade', and help engineering students to obtain full benefit of modeling experience.

8.5 CONTRIBUTION

Modeling is a fundamental aspect of engineering; and the study of modeling in engineering education is a growing area of research. The overarching objective of this dissertation is to understand the differences between engineering students' modeling practices; and indirectly improving the modeling abilities and performance of engineering students through this understanding.

Although substantial amount of literature has recently been devoted to investigate the factors involved in modeling practices, such studies have been primarily in the domain of mathematics and physics. In the engineering education field, although there is a recent emphasis, there are few studies that investigate modeling. As a result, the differences between the modeling practices of engineers and those of other disciplines remain an under-researched area of engineering. This dissertation thus begins to fill in a gap in the engineering education literature by investigating the engineering students' modeling process.

The contributions of this dissertation to the field of engineering can be listed as follows: The dissertation starts with a search of the relevant literature in modeling, and links the current findings in modeling to the engineering arena. The objective of this undertaking is to initiate a conversation in engineering about the importance of modeling and modeling instruction.

A second contribution of this dissertation is measuring the growth of modeling outcomes along seven distinct stages. Although instructors theoretically would expect an incremental growth in modeling, until now, there have been no studies that documented the type and extent of change. We observe, in general, a concave curve in modeling stages, with validation and verification being significantly under-developed, compared to other stages.

In measuring the change of growth, a significant effort was devoted to data collection. The instruments, including model-eliciting activities and the surveys, were embedded in course curriculum. Students were given the instruments coinciding with their instruction; hence, data collection lasted an academic year and included both sophomores and seniors. Longitudinal data collection is an expensive methodology in terms of time, and few studies in engineering education have collected such data over a course of a year. In addition, the analysis of the data included both quantitative and qualitative approaches.

A third contribution of this dissertation to the literature of engineering and education is the development of an Engineering Modeling Self-efficacy Scale. The impact of self-efficacy is widely measured in almost every area using specific self-efficacy instruments, such as design self-efficacy (Carberry et al. 2010), tinkering self-efficacy (Baker, Krause and Purzer 2008, Richardson 2008), self-efficacy of engineering and computer use (Hutchinson et al. 2006, Marra and Bogue 2006, Amato-Henderson et al. 2007, Shull and Weiner 2002); as well as generalized self-efficacy in engineering instruments but modeling self-efficacy has not been measured, and there are currently no other instruments to measure self-efficacy in modeling. By creating the instrument, this dissertation opens a way for future work in self-efficacy and modeling.

The fourth and most significant contribution of this dissertation is estimating the impact of self-efficacy, epistemology and metacognition on modeling ability development. That is, this is the first study to focus on the relationship between these constructs and modeling. Different from other research, we are focusing on the impact of self-efficacy, epistemology and metacognition on change, as opposed to studies that measure the correlation between the level and the modeling outcome, or correlation between the extent of change in these three constructs and the change in modeling outcome.

The final contribution of this dissertation is to document the strategies of modeling from resulting MEA reports as well as coded student interviews. The investigation of the MEA reports provides a contribution to the ongoing research on MEAs and modeling. Universities across the U.S., including but not limited to the University of Pittsburgh, Purdue University, U.S. Air Force Academy, Colorado School of Mines, California Poly San Luis Obispo and the University of Minnesota have used many of these modeling cases and have integrated them into their educational programs.

By providing a guide on the relationship between these cases and the three specific cognitive constructs, this dissertation will assist scholars in their future work on creating and implementing new engineering MEAs.

The dissertation is timely and relevant to the engineering community for several reasons. Schoenfeld (1992) suggests that there are two important issues that remain unresolved in learning how to think mathematically - one is consideration of cognitive factors that play a role in the process and the other one is extending the mathematical thinking situations beyond problem solving. This dissertation responds to both, which, in the past 18 years still remain unresolved. By demonstrating the impact that self-efficacy, epistemic beliefs and metacognition impact modeling ability growth; we indicate that to reach the full potential of educational interventions, additional parameters should be integrated into engineering education to guarantee students' cognitive development. This argument is potentially discordant to the current engineering education practice; and thus this research can play an important role in initiating a dialogue in the future direction of engineering education.

APPENDIX A

ENGINEERING MODELING SELF-EFFICACY SCALE

Instructions

Please think of a real life **SYSTEM** that you would be expected to build or design within your engineering discipline (e.g. bridges, buildings, an automobile, a machine, a factory, a computer software etc.)

Assume that you are building a model of this system (such as a physical or symbolic model, like a mathematical or computer simulation representation), and that you are the only one in charge of the following tasks. Sincerely rate how well you think you can do each of them.

ENGINEERING MODELING SELF-EFFICACY SCALE						
ITEMS		**Cannot do at all**	**Can do Poorly**	**Can do Just OK**	**Can do Well**	**Can do Very Well**
1	Decide what data is necessary to use in the model.					
2	Search databases to find necessary data.					
3	Determine whether the collected/given data sample is representative of the population.					
4	Decide whether the data is reliable and sample size is large enough.					
5	Identify which parts of the dataset are relevant to the model.					
6	Develop/use a method to estimate missing data.					
7	Create a schematic representation of the system in two or three dimensions (create a prototype).					
8	List the sub-processes within the system (e.g. physical, biological, and/or chemical, economical relationships, etc.)					
9	Identify the relationships between sub-processes (how changes in one affect changes another).					
10	Identify inputs and outputs of the system.					
11	Determine the (initial and boundary) conditions for the system to start/ stop functioning.					
12	Determine the necessary conditions for a system to exist/ survive once started functioning.					
13	Predict how the system will function in extreme cases.					
14	Determine the criteria to decide if the model performs well.					
15	Determine whether the performance criteria chosen are appropriate for the system.					
16	Find ways to modify the performance criteria to make it better.					
17	Quantify the impact of sub-processes on the performance criteria (goal of the model).					
18	Simplify the relationships between processes that exist in the system.					
19	Identify the variables and parameters in a model.					

20	Identify the constraints on the model.					
21	Write a computer program to calculate the outcomes of the model.					
22	Choose a mathematical/ statistical model to calculate the performance criteria/ results of a developed model.					
23	Calculate the outcomes of the model by hand.					
24	Calculate the outcomes of the model using a computer code.					
25	Create tables and graphs of the results (manual or computerized).					
26	Determine the uncertainty in the parameters and data.					
27	Conduct a sensitivity analysis on the numerical results.					
28	Understand/ evaluate the results of a calculational model					
29	Determine if the results indicate an error.					
30	Use the results to predict future behavior of the system.					
31	Determine if the uncertainty in results indicates a need for an update or redesign of the model.					
32	Explain how the results of a calculational model are obtained.					
33	Determine qualitatively if the developed model looks 'alright'.					
34	Determine numerically if the model results are valid.					
35	Determine ways to measure if the created model generates results in line with the actual system.					
36	Determine how the model developed compares to other models of the same system.					

APPENDIX B

EPISTEMIC BELIEFS INVENTORY

ITEMS	COMPLETELY DISAGREE (1)	DISAGREE	NEUTRAL	AGREE	COMPLETELY AGREE(5)
1. It bothers me when instructors don't tell students the answers to complicated problems.					
2. Truth means different things to different people.* †					
3. Students who learn things quickly are the most successful.					
4. People should always obey the law.					
5. Some people will never be smart no matter how hard they work.					
6. Absolute moral truth does not exist.* †					
7. Parents should teach their children all there is to know about life. †					
8. Really smart students don't have to work as hard to do well in school.					
9. If a person tries too hard to understand a problem, they will most likely end up being confused.					

Epistemic Beliefs Inventory (Continued)

10. Too many theories just complicate things. †
11. The best ideas are often the most simple.
12. People can’t do too much about how smart they are.
13. Instructors should focus on facts instead of theories.
14. I like teachers who present several competing theories and let their students decide which is best.* †
15. How well you do in school depends on how smart you are.
16. If you don’t learn something quickly, you won’t ever learn it.
17. Some people just have a knack for learning and others don’t.
18. Things are simpler than most professors would have you believe. †
19. If two people are arguing about something, at least one of them must be wrong.
20. Children should be allowed to question their parents’ authority.* †
21. If you haven’t understood a chapter the first time through, going back over it won’t help.
22. Science is easy to understand because it contains so many facts.
23. The moral rules i live by apply to everyone.
24. The more you know about a topic, the more there is to know.*
25. What is true today will be true tomorrow.
26. Smart people are born that way.
27. When someone in authority tells me what to do, i usually do it.
28. People who question authority are trouble makers.
29. Working on a problem with no quick solution is a waste of time.
30. You can study something for years and still not really understand it.*
31. Sometimes there are no right answers to life’s big problems.*
32. Some people are born with special gifts and talents. †

APPENDIX C

METACOGNITIVE INVENTORY

Please select the answer that best reflects your thinking when you are working on an exercise/ homework.

	ITEMS	Not At All	Mostly Not	Just OK	Mostly Yes	At All Times
1	I am always aware of my own thinking.					
2	I always double check my work.					
3	I attempt to discover the main ideas in an exercise.					
4	I try to understand the goals of an exercise before I attempt to solve it.					
5	I am aware of what modeling/ problem solving strategies to use and when to use them to in order to solve an exercise.					
6	If I realize an error while working on an exercise, I always correct it.					
7	I ask myself how an exercise is related to what I already know.					
8	I try to understand what the solution to an exercise requires.					

	Metacognitive Inventory (Continued)					
9	I am aware of the need to plan my course of action in advance to solving an exercise.					
10	I know how much of the solution I have left to complete an assignment.					
11	I think through the meaning of an exercise before I begin to solve it.					
12	I make sure I understand just what needs to be done to solve an exercise and how to do it.					
13	I am aware of my ongoing thinking.					
14	I keep track of my progress and, if necessary, I change my solution method.					
15	I use multiple solution methods to solve an exercise.					
16	I determine how to solve an exercise from the questions in an exercise.					
17	I am aware of my trying to understand an exercise before I attempt to solve it.					
18	I check my accuracy as I progress through the solution.					
19	I select and organize relevant information before starting to solve an exercise.					
20	I try to understand what is asked of me before I attempt to solve an exercise.					

Note: The instrument is adapted from O'Neill and Abedi (1996) with some changes. The wording of the items has been changed to include the words modeling and exercise to better fit the context of the modeling and engineering classrooms, and the measurement is generalized to general habits as opposed to a single time or single exercise.

APPENDIX D

CORRELATIONS BETWEEN THE CONSTRUCTS

Note: Numbers in each cell represent the following from top to bottom respectively:
Pearson Correlation Coefficients, Prob > |r| under H0: Rho=0 and the Number of Observations

Variables								
	RED	**CON**	**EPS**	**CAL**	**CUS**	**RE**	**VV**	**SE_{RED}**
RED	1.00000 198	0.70833 <.0001 198	0.55590 <.0001 198	0.65886 <.0001 198	0.47213 <.0001 198	0.58827 <.0001 198	0.35283 <.0001 198	-0.02678 0.7080 198
CON	0.70833 <.0001 198	1.00000 198	0.66317 <.0001 198	0.75976 <.0001 198	0.63766 <.0001 198	0.55608 <.0001 198	0.47843 <.0001 198	-0.02735 0.7021 198
EPS	0.55590 <.0001 198	0.66317 <.0001 198	1.00000 198	0.68864 <.0001 198	0.69842 <.0001 198	0.61399 <.0001 198	0.46633 <.0001 198	0.06205 0.3851 198
CAL	0.65886 <.0001 198	0.75976 <.0001 198	0.68864 <.0001 198	1.00000 198	0.64523 <.0001 198	0.49910 <.0001 198	0.35830 <.0001 198	0.04540 0.5253 198
CUS	0.47213 <.0001 198	0.63766 <.0001 198	0.69842 <.0001 198	0.64523 <.0001 198	1.00000 198	0.57506 <.0001 198	0.46321 <.0001 198	0.06038 0.3981 198
RE	0.58827 <.0001 198	0.55608 <.0001 198	0.61399 <.0001 198	0.49910 <.0001 198	0.57506 <.0001 198	1.00000 198	0.27095 0.0001 198	0.00653 0.9273 198
VV	0.35283 <.0001 198	0.47843 <.0001 198	0.46633 <.0001 198	0.35830 <.0001 198	0.46321 <.0001 198	0.27095 0.0001 198	1.00000 198	-0.04334 0.5443 198
SE_{RED}	-0.02678 0.7080 198	-0.02735 0.7021 198	0.06205 0.3851 198	0.04540 0.5253 198	0.06038 0.3981 198	0.00653 0.9273 198	-0.04334 0.5443 198	1.00000 198

Variables								
	RED	**CON**	**EPS**	**CAL**	**CUS**	**RE**	**VV**	**SE_{RED}**
SE_{PM}	-0.07691 0.2815 198	-0.02377 0.7396 198	-0.04558 0.5237 198	-0.05339 0.4551 198	-0.04920 0.4912 198	-0.03833 0.5918 198	0.02882 0.6869 198	0.17230 0.0152 198
SE_{CON}	-0.09516 0.1824 198	-0.03373 0.6371 198	0.01915 0.7889 198	0.05358 0.4535 198	0.02056 0.7737 198	-0.06009 0.4004 198	0.03705 0.6043 198	0.19330 0.0064 198
SE_{EPS}	-0.00614 0.9316 198	0.01988 0.7810 198	0.05304 0.4580 198	-0.00397 0.9557 198	0.06773 0.3431 198	0.05834 0.4143 198	0.06109 0.3926 198	0.35102 <.0001 198
SE_{IE}	0.05978 0.4028 198	-0.02108 0.7682 198	-0.03891 0.5862 198	-0.02970 0.6779 198	0.01878 0.7928 198	0.03433 0.6311 198	0.00219 0.9756 198	0.36495 <.0001 198
SE_{CAL}	0.04953 0.4883 198	-0.01496 0.8343 198	0.01095 0.8783 198	-0.00077 0.9914 198	0.02193 0.7591 198	0.04614 0.5186 198	0.01853 0.7955 198	0.09134 0.2006 198
SE_{UV}	0.04818 0.5003 198	-0.01018 0.8868 198	0.06673 0.3502 198	0.06134 0.3906 198	0.08007 0.2621 198	0.08294 0.2454 198	0.04025 0.5734 198	0.23217 0.0010 198
Fixed Ability	-0.07671 0.2828 198	-0.04163 0.5603 198	-0.07304 0.3065 198	-0.05223 0.4649 198	0.03771 0.5979 198	-0.03961 0.5795 198	-0.04913 0.4919 198	-0.04114 0.5650 198
Quick Learning	-0.12150 0.0882 198	-0.08140 0.2543 198	-0.06109 0.3926 198	-0.11134 0.1184 198	0.05045 0.4803 198	-0.04685 0.5122 198	-0.01137 0.8737 198	-0.06328 0.3758 198
Omniscient Authority	0.01146 0.8727 198	-0.04724 0.5087 198	0.00604 0.9327 198	0.02541 0.7223 198	0.03328 0.6416 198	-0.03569 0.6176 198	-0.04026 0.5733 198	0.11600 0.1036 198
Simple Knowledge	0.01576 0.8255 198	-0.08722 0.2218 198	0.05936 0.4061 198	0.03871 0.5882 198	-0.12960 0.0688 198	-0.02743 0.7012 198	0.06579 0.3571 198	-0.01950 0.7851 198
Certain Knowledge	0.05598 0.4334 198	-0.05832 0.4144 198	0.03297 0.6447 198	-0.03594 0.6152 198	0.01678 0.8145 198	0.05875 0.4110 198	-0.02412 0.7358 198	-0.14762 0.0379 198
Awareness	0.03370 0.6607 172	-0.08948 0.2431 172	0.08152 0.2877 172	0.07346 0.3382 172	0.07738 0.3130 172	0.00676 0.9298 172	0.05905 0.4416 172	0.46099 <.0001 172
Self-checking	0.07505 0.3279 172	-0.01438 0.8515 172	0.13456 0.0784 172	0.13251 0.0831 172	0.10101 0.1874 172	0.13184 0.0847 172	0.09265 0.2267 172	0.40405 <.0001 172

Variables								
	RED	**CON**	**EPS**	**CAL**	**CUS**	**RE**	**VV**	**SE_{RED}**
Cognitive Strategy	0.03867 0.6145 172	-0.06431 0.4020 172	0.09508 0.2147 172	0.13631 0.0746 172	0.04982 0.5163 172	-0.00102 0.9894 172	-0.01830 0.8117 172	0.28577 0.0001 172
Planning	-0.00476 0.9506 172	0.00538 0.9442 172	0.07151 0.3512 172	0.14388 0.0597 172	0.09457 0.2172 172	0.00506 0.9475 172	0.06667 0.3849 172	0.53707 <.0001 172

Variables							
	SE_{PM}	**SE_{CON}**	**SE_{EPS}**	**SE_{IE}**	**SE_{CAL}**	**SE_{UV}**	**Fixed Ability**
RED	-0.07691 0.2815 198	-0.09516 0.1824 198	-0.00614 0.9316 198	0.05978 0.4028 198	0.04953 0.4883 198	0.04818 0.5003 198	-0.07671 0.2828 198
CON	-0.02377 0.7396 198	-0.03373 0.6371 198	0.01988 0.7810 198	-0.02108 0.7682 198	-0.01496 0.8343 198	-0.01018 0.8868 198	-0.04163 0.5603 198
EPS	-0.04558 0.5237 198	0.01915 0.7889 198	0.05304 0.4580 198	-0.03891 0.5862 198	0.01095 0.8783 198	0.06673 0.3502 198	-0.07304 0.3065 198
CAL	-0.05339 0.4551 198	0.05358 0.4535 198	-0.00397 0.9557 198	-0.02970 0.6779 198	-0.00077 0.9914 198	0.06134 0.3906 198	-0.05223 0.4649 198
CUS	-0.04920 0.4912 198	0.02056 0.7737 198	0.06773 0.3431 198	0.01878 0.7928 198	0.02193 0.7591 198	0.08007 0.2621 198	0.03771 0.5979 198
RE	-0.03833 0.5918 198	-0.06009 0.4004 198	0.05834 0.4143 198	0.03433 0.6311 198	0.04614 0.5186 198	0.08294 0.2454 198	-0.03961 0.5795 198
VV	0.02882 0.6869 198	0.03705 0.6043 198	0.06109 0.3926 198	0.00219 0.9756 198	0.01853 0.7955 198	0.04025 0.5734 198	-0.04913 0.4919 198
SE_{RED}	0.17230 0.0152 198	0.19330 0.0064 198	0.35102 <.0001 198	0.36495 <.0001 198	0.09134 0.2006 198	0.23217 0.0010 198	-0.04114 0.5650 198
SE_{PM}	1.00000 198	0.24937 0.0004 198	0.34721 <.0001 198	0.44183 <.0001 198	0.47586 <.0001 198	0.33308 <.0001 198	-0.00332 0.9630 198
SE_{CON}	0.24937 0.0004 198	1.00000 198	0.20699 0.0034 198	0.21138 0.0028 198	0.14535 0.0410 198	0.46455 <.0001 198	-0.07561 0.2897 198

Variables							
	SE_{PM}	SE_{CON}	SE_{EPS}	SE_{IE}	SE_{CAL}	SE_{UV}	**Fixed Ability**
SE_{EPS}	0.34721 <.0001 198	0.20699 0.0034 198	1.00000 198	0.40864 <.0001 198	0.30133 <.0001 198	0.29404 <.0001 198	0.00654 0.9272 198
SE_{IE}	0.44183 <.0001 198	0.21138 0.0028 198	0.40864 <.0001 198	1.00000 198	0.57824 <.0001 198	0.61808 <.0001 198	-0.05625 0.4312 198
SE_{CAL}	0.47586 <.0001 198	0.14535 0.0410 198	0.30133 <.0001 198	0.57824 <.0001 198	1.00000 198	0.36146 <.0001 198	-0.12501 0.0793 198
SE_{UV}	0.33308 <.0001 198	0.46455 <.0001 198	0.29404 <.0001 198	0.61808 <.0001 198	0.36146 <.0001 198	1.00000 198	0.05443 0.4463 198
Fixed Ability	-0.00332 0.9630 198	-0.07561 0.2897 198	0.00654 0.9272 198	-0.05625 0.4312 198	-0.12501 0.0793 198	0.05443 0.4463 198	1.00000 198
Quick Learning	0.06592 0.3562 198	0.04759 0.5056 198	0.19329 0.0064 198	-0.08816 0.2168 198	-0.03209 0.6535 198	0.07711 0.2803 198	0.56322 <.0001 198
Omniscient Authority	-0.26583 0.0002 198	0.00195 0.9782 198	0.05840 0.4138 198	0.03138 0.6608 198	-0.21361 0.0025 198	-0.01012 0.8875 198	0.08217 0.2498 198
Simple Knowledge	-0.14097 0.0476 198	-0.08952 0.2098 198	-0.09578 0.1795 198	-0.09974 0.1621 198	-0.14351 0.0437 198	-0.04247 0.5524 198	0.10701 0.1335 198
Certain Knowledge	-0.03501 0.6243 198	-0.14699 0.0388 198	0.09303 0.1924 198	-0.18902 0.0077 198	-0.15249 0.0320 198	-0.03407 0.6338 198	0.49928 <.0001 198
Awareness	0.20235 0.0078 172	0.39555 <.0001 172	0.12934 0.0908 172	0.41212 <.0001 172	0.13933 0.0683 172	0.57891 <.0001 172	-0.03780 0.6225 172
Self-checking	0.35365 <.0001 172	0.35549 <.0001 172	0.21727 0.0042 172	0.29100 0.0001 172	0.39158 <.0001 172	0.49074 <.0001 172	-0.09659 0.2075 172
Cognitive Strategy	0.14793 0.0528 172	0.42831 <.0001 172	-0.07070 0.3567 172	0.29795 <.0001 172	0.14778 0.0530 172	0.53409 <.0001 172	-0.16756 0.0280 172
Planning	0.19463 0.0105 172	0.39552 <.0001 172	0.13160 0.0853 172	0.25358 0.0008 172	0.09316 0.2242 172	0.36975 <.0001 172	0.02342 0.7604 172

Variables				
	Quick Learning	**Omniscient Authority**	**Simple Knowledge**	**Certain Knowledge**
RED	-0.12150 0.0882 198	0.01146 0.8727 198	0.01576 0.8255 198	0.05598 0.4334 198
CON	-0.08140 0.2543 198	-0.04724 0.5087 198	-0.08722 0.2218 198	-0.05832 0.4144 198
EPS	-0.06109 0.3926 198	0.00604 0.9327 198	0.05936 0.4061 198	0.03297 0.6447 198
CAL	-0.11134 0.1184 198	0.02541 0.7223 198	0.03871 0.5882 198	-0.03594 0.6152 198
CUS	0.05045 0.4803 198	0.03328 0.6416 198	-0.12960 0.0688 198	0.01678 0.8145 198
RE	-0.04685 0.5122 198	-0.03569 0.6176 198	-0.02743 0.7012 198	0.05875 0.4110 198
VV	-0.01137 0.8737 198	-0.04026 0.5733 198	0.06579 0.3571 198	-0.02412 0.7358 198
SE_{RED}	-0.06328 0.3758 198	0.11600 0.1036 198	-0.01950 0.7851 198	-0.14762 0.0379 198
SE_{PM}	0.06592 0.3562 198	-0.26583 0.0002 198	-0.14097 0.0476 198	-0.03501 0.6243 198
SE_{CON}	0.04759 0.5056 198	0.00195 0.9782 198	-0.08952 0.2098 198	-0.14699 0.0388 198
SE_{EPS}	0.19329 0.0064 198	0.05840 0.4138 198	-0.09578 0.1795 198	0.09303 0.1924 198
SE_{IE}	-0.08816 0.2168 198	0.03138 0.6608 198	-0.09974 0.1621 198	-0.18902 0.0077 198
SE_{CAL}	-0.03209 0.6535 198	-0.21361 0.0025 198	-0.14351 0.0437 198	-0.15249 0.0320 198
SE_{UV}	0.07711 0.2803 198	-0.01012 0.8875 198	-0.04247 0.5524 198	-0.03407 0.6338 198

Variables				
	Quick Learning	**Omniscient Authority**	**Simple Knowledge**	**Certain Knowledge**
Fixed Ability	0.56322 <.0001 198	0.08217 0.2498 198	0.10701 0.1335 198	0.49928 <.0001 198
Quick Learning	1.00000 198	0.26654 0.0001 198	0.12715 0.0743 198	0.50190 <.0001 198
Omniscient Authority	0.26654 0.0001 198	1.00000 198	0.15682 0.0274 198	0.11705 0.1005 198
Simple Knowledge	0.12715 0.0743 198	0.15682 0.0274 198	1.00000 198	0.22476 0.0015 198
Certain Knowledge	0.50190 <.0001 198	0.11705 0.1005 198	0.22476 0.0015 198	1.00000 198
Awareness	0.04942 0.5197 172	0.20033 0.0084 172	0.00719 0.9254 172	-0.08270 0.2808 172
Self-checking	-0.11417 0.1359 172	0.03974 0.6047 172	-0.16910 0.0266 172	-0.23863 0.0016 172
Cognitive Strategy	-0.13377 0.0802 172	0.22782 0.0027 172	-0.00958 0.9008 172	-0.09485 0.2158 172
Planning	-0.16673 0.0288 172	0.15069 0.0485 172	-0.12166 0.1119 172	-0.11987 0.1173 172

Variables				
	Awareness	**Self-checking**	**Cognitive Strategy**	**Planning**
RED	0.03370 0.6607 172	0.07505 0.3279 172	0.03867 0.6145 172	-0.00476 0.9506 172
CON	-0.08948 0.2431 172	-0.01438 0.8515 172	-0.06431 0.4020 172	0.00538 0.9442 172
EPS	0.08152 0.2877 172	0.13456 0.0784 172	0.09508 0.2147 172	0.07151 0.3512 172
CAL	0.07346 0.3382 172	0.13251 0.0831 172	0.13631 0.0746 172	0.14388 0.0597 172
CUS	0.07738 0.3130 172	0.10101 0.1874 172	0.04982 0.5163 172	0.09457 0.2172 172
RE	0.00676 0.9298 172	0.13184 0.0847 172	-0.00102 0.9894 172	0.00506 0.9475 172
VV	0.05905 0.4416 172	0.09265 0.2267 172	-0.01830 0.8117 172	0.06667 0.3849 172
SE_{RED}	0.46099 <.0001 172	0.40405 <.0001 172	0.28577 0.0001 172	0.53707 <.0001 172
SE_{PM}	0.20235 0.0078 172	0.35365 <.0001 172	0.14793 0.0528 172	0.19463 0.0105 172
SE_{CON}	0.39555 <.0001 172	0.35549 <.0001 172	0.42831 <.0001 172	0.39552 <.0001 172
SE_{EPS}	0.12934 0.0908 172	0.21727 0.0042 172	-0.07070 0.3567 172	0.13160 0.0853 172
SE_{IE}	0.41212 <.0001 172	0.29100 0.0001 172	0.29795 <.0001 172	0.25358 0.0008 172
SE_{CAL}	0.13933 0.0683 172	0.39158 <.0001 172	0.14778 0.0530 172	0.09316 0.2242 172
SE_{UV}	0.57891 <.0001 172	0.49074 <.0001 172	0.53409 <.0001 172	0.36975 <.0001 172

Variables				
	Awareness	Self-checking	Cognitive Strategy	Planning
Fixed Ability	-0.03780 0.6225 172	-0.09659 0.2075 172	-0.16756 0.0280 172	0.02342 0.7604 172
Quick Learning	0.04942 0.5197 172	-0.11417 0.1359 172	-0.13377 0.0802 172	-0.16673 0.0288 172
Omniscient Authority	0.20033 0.0084 172	0.03974 0.6047 172	0.22782 0.0027 172	0.15069 0.0485 172
Simple Knowledge	0.00719 0.9254 172	-0.16910 0.0266 172	-0.00958 0.9008 172	-0.12166 0.1119 172
Certain Knowledge	-0.08270 0.2808 172	-0.23863 0.0016 172	-0.09485 0.2158 172	-0.11987 0.1173 172
Awareness	1.00000 172	0.65544 <.0001 172	0.75258 <.0001 172	0.63380 <.0001 172
Self-checking	0.65544 <.0001 172	1.00000 172	0.56232 <.0001 172	0.58539 <.0001 172
Cognitive Strategy	0.75258 <.0001 172	0.56232 <.0001 172	1.00000 172	0.67613 <.0001 172
Planning	0.63380 <.0001 172	0.58539 <.0001 172	0.67613 <.0001 172	1.00000 172

Variables				
	Awareness	**Self-checking**	**Cognitive Strategy**	**Planning**
RED	0.03370 0.6607 172	0.07505 0.3279 172	0.03867 0.6145 172	-0.00476 0.9506 172
CON	-0.08948 0.2431 172	-0.01438 0.8515 172	-0.06431 0.4020 172	0.00538 0.9442 172
EPS	0.08152 0.2877 172	0.13456 0.0784 172	0.09508 0.2147 172	0.07151 0.3512 172
CAL	0.07346 0.3382 172	0.13251 0.0831 172	0.13631 0.0746 172	0.14388 0.0597 172
CUS	0.07738 0.3130 172	0.10101 0.1874 172	0.04982 0.5163 172	0.09457 0.2172 172
RE	0.00676 0.9298 172	0.13184 0.0847 172	-0.00102 0.9894 172	0.00506 0.9475 172
VV	0.05905 0.4416 172	0.09265 0.2267 172	-0.01830 0.8117 172	0.06667 0.3849 172
SE_{RED}	0.46099 <.0001 172	0.40405 <.0001 172	0.28577 0.0001 172	0.53707 <.0001 172
SE_{PM}	0.20235 0.0078 172	0.35365 <.0001 172	0.14793 0.0528 172	0.19463 0.0105 172
SE_{CON}	0.39555 <.0001 172	0.35549 <.0001 172	0.42831 <.0001 172	0.39552 <.0001 172
SE_{EPS}	0.12934 0.0908 172	0.21727 0.0042 172	-0.07070 0.3567 172	0.13160 0.0853 172
SE_{IE}	0.41212 <.0001 172	0.29100 0.0001 172	0.29795 <.0001 172	0.25358 0.0008 172
SE_{CAL}	0.13933 0.0683 172	0.39158 <.0001 172	0.14778 0.0530 172	0.09316 0.2242 172
SE_{UV}	0.57891 <.0001 172	0.49074 <.0001 172	0.53409 <.0001 172	0.36975 <.0001 172

Variables				
	Awareness	**Self-checking**	**Cognitive Strategy**	**Planning**
Fixed Ability	-0.03780 0.6225 172	-0.09659 0.2075 172	-0.16756 0.0280 172	0.02342 0.7604 172
Quick Learning	0.04942 0.5197 172	-0.11417 0.1359 172	-0.13377 0.0802 172	-0.16673 0.0288 172
Omniscient Authority	0.20033 0.0084 172	0.03974 0.6047 172	0.22782 0.0027 172	0.15069 0.0485 172
Simple Knowledge	0.00719 0.9254 172	-0.16910 0.0266 172	-0.00958 0.9008 172	-0.12166 0.1119 172
Certain Knowledge	-0.08270 0.2808 172	-0.23863 0.0016 172	-0.09485 0.2158 172	-0.11987 0.1173 172
Awareness	1.00000 172	0.65544 <.0001 172	0.75258 <.0001 172	0.63380 <.0001 172
Self-checking	0.65544 <.0001 172	1.00000 172	0.56232 <.0001 172	0.58539 <.0001 172
Cognitive Strategy	0.75258 <.0001 172	0.56232 <.0001 172	1.00000 172	0.67613 <.0001 172
Planning	0.63380 <.0001 172	0.58539 <.0001 172	0.67613 <.0001 172	1.00000 172

APPENDIX E

GROWTH MODELS TESTED

Independent Variable	Dependent Variables	Control Variables
RED	Month	
RED	Month, $Month^2$	
RED	Month, $Month^2$, $Month^3$	
RED	$Month^2$	
RED	$Month^3$	
RED	Month	Gender
RED	Month, $Month^2$	Gender
RED	Month, $Month^2$, $Month^3$	Gender
RED	$Month^2$	Gender
RED	$Month^3$	Gender
RED	Month	CGPA
RED	Month, $Month^2$	CGPA
RED	Month, $Month^2$, $Month^3$	CGPA
RED	$Month^2$	CGPA
RED	$Month^3$	CGPA
RED	Month,	MEA
RED	Month, $Month^2$	MEA
RED	Month, $Month^2$, $Month^3$	MEA
RED	$Month^2$	MEA

Independent Variable	**Dependent Variables**	**Control Variables**
RED	$Month^3$	MEA
RED	Month,	MEA, Gender, GPA
RED	Month, $Month^2$	MEA, Gender, GPA
RED	Month, $Month^2$, $Month^3$	MEA, Gender, GPA
RED	$Month^2$	MEA, Gender, GPA
RED	$Month^3$	MEA, Gender, GPA
CON	Month	
CON	Month, $Month^2$	
CON	Month, $Month^2$, $Month^3$	
CON	$Month^2$	
CON	$Month^3$	
CON	Month	Gender
CON	Month, $Month^2$	Gender
CON	Month, $Month^2$, $Month^3$	Gender
CON	$Month^2$	Gender
CON	$Month^3$	Gender
CON	Month	CGPA
CON	Month, $Month^2$	CGPA
CON	Month, $Month^2$, $Month^3$	CGPA
CON	$Month^2$	CGPA
CON	$Month^3$	CGPA
CON	Month,	MEA
CON	Month, $Month^2$	MEA
CON	Month, $Month^2$, $Month^3$	MEA
CON	$Month^2$	MEA
CON	$Month^3$	MEA
CON	Month,	MEA, Gender, GPA
CON	Month, $Month^2$	MEA, Gender, GPA
CON	Month, $Month^2$, $Month^3$	MEA, Gender, GPA
CON	$Month^2$	MEA, Gender, GPA
CON	$Month^3$	MEA, Gender, GPA
CON	Month	

Independent Variable	Dependent Variables	Control Variables
CON	Month, $Month^2$	
CON	Month, $Month^2$, $Month^3$	
CON	$Month^2$	
CON	$Month^3$	
CON	Month	Gender
CON	Month, $Month^2$	Gender
CON	Month, $Month^2$, $Month^3$	Gender
CON	$Month^2$	Gender
CON	$Month^3$	Gender
CON	Month	CGPA
CON	Month, $Month^2$	CGPA
CON	Month, $Month^2$, $Month^3$	CGPA
CON	$Month^2$	CGPA
CON	$Month^3$	CGPA
CON	Month,	MEA
CON	Month, $Month^2$	MEA
CON	Month, $Month^2$, $Month^3$	MEA
CON	$Month^2$	MEA
CON	$Month^3$	MEA
CON	Month,	MEA, Gender, GPA
CON	Month, $Month^2$	MEA, Gender, GPA
CON	Month, $Month^2$, $Month^3$	MEA, Gender, GPA
CON	$Month^2$	MEA, Gender, GPA
CON	$Month^3$	MEA, Gender, GPA
EPS	Month	
EPS	Month, $Month^2$	
EPS	Month, $Month^2$, $Month^3$	
EPS	$Month^2$	
EPS	$Month^3$	
EPS	Month	Gender
EPS	Month, $Month^2$	Gender
EPS	Month, $Month^2$, $Month^3$	Gender

Independent Variable	**Dependent Variables**	**Control Variables**
EPS	$Month^2$	Gender
EPS	$Month^3$	Gender
EPS	Month	CGPA
EPS	Month, $Month^2$	CGPA
EPS	Month, $Month^2$, $Month^3$	CGPA
EPS	$Month^2$	CGPA
EPS	$Month^3$	CGPA
EPS	Month,	MEA
EPS	Month, $Month^2$	MEA
EPS	Month, $Month^2$, $Month^3$	MEA
EPS	$Month^2$	MEA
EPS	$Month^3$	MEA
EPS	Month,	MEA, Gender, GPA
EPS	Month, $Month^2$	MEA, Gender, GPA
EPS	Month, $Month^2$, $Month^3$	MEA, Gender, GPA
EPS	$Month^2$	MEA, Gender, GPA
EPS	$Month^3$	MEA, Gender, GPA
CAL	Month	
CAL	Month, $Month^2$	
CAL	Month, $Month^2$, $Month^3$	
CAL	$Month^2$	
CAL	$Month^3$	
CAL	Month	Gender
CAL	Month, $Month^2$	Gender
CAL	Month, $Month^2$, $Month^3$	Gender
CAL	$Month^2$	Gender
CAL	$Month^3$	Gender
CAL	Month	CGPA
CAL	Month, $Month^2$	CGPA
CAL	Month, $Month^2$, $Month^3$	CGPA
CAL	$Month^2$	CGPA
CAL	$Month^3$	CGPA

Independent Variable	**Dependent Variables**	**Control Variables**
CAL	Month,	MEA
CAL	Month, $Month^2$	MEA
CAL	Month, $Month^2$, $Month^3$	MEA
CAL	$Month^2$	MEA
CAL	$Month^3$	MEA
CAL	Month,	MEA, Gender, GPA
CAL	Month, $Month^2$	MEA, Gender, GPA
CAL	Month, $Month^2$, $Month^3$	MEA, Gender, GPA
CAL	$Month^2$	MEA, Gender, GPA
CAL	$Month^3$	MEA, Gender, GPA
CUS	Month	
CUS	Month, $Month^2$	
CUS	Month, $Month^2$, $Month^3$	
CUS	$Month^2$	
CUS	$Month^3$	
CUS	Month	Gender
CUS	Month, $Month^2$	Gender
CUS	Month, $Month^2$, $Month^3$	Gender
CUS	$Month^2$	Gender
CUS	$Month^3$	Gender
CUS	Month	CGPA
CUS	Month, $Month^2$	CGPA
CUS	Month, $Month^2$, $Month^3$	CGPA
CUS	$Month^2$	CGPA
CUS	$Month^3$	CGPA
CUS	Month,	MEA
CUS	Month, $Month^2$	MEA
CUS	Month, $Month^2$, $Month^3$	MEA
CUS	$Month^2$	MEA
CUS	$Month^3$	MEA
CUS	Month,	MEA, Gender, GPA
CUS	Month, $Month^2$	MEA, Gender, GPA

Independent Variable	**Dependent Variables**	**Control Variables**
CUS	Month, $Month^2$, $Month^3$	MEA, Gender, GPA
CUS	$Month^2$	MEA, Gender, GPA
CUS	$Month^3$	MEA, Gender, GPA
RE	Month	
RE	Month, $Month^2$	
RE	Month, $Month^2$, $Month^3$	
RE	$Month^2$	
RE	$Month^3$	
RE	Month	Gender
RE	Month, $Month^2$	Gender
RE	Month, $Month^2$, $Month^3$	Gender
RE	$Month^2$	Gender
RE	$Month^3$	Gender
RE	Month	CGPA
RE	Month, $Month^2$	CGPA
RE	Month, $Month^2$, $Month^3$	CGPA
RE	$Month^2$	CGPA
RE	$Month^3$	CGPA
RE	Month,	MEA
RE	Month, $Month^2$	MEA
RE	Month, $Month^2$, $Month^3$	MEA
RE	$Month^2$	MEA
RE	$Month^3$	MEA
RE	Month,	MEA, Gender, GPA
RE	Month, $Month^2$	MEA, Gender, GPA
RE	Month, $Month^2$, $Month^3$	MEA, Gender, GPA
RE	$Month^2$	MEA, Gender, GPA
RE	$Month^3$	MEA, Gender, GPA
VV	Month	
VV	Month, $Month^2$	
VV	Month, $Month^2$, $Month^3$	
VV	$Month^2$	

Independent Variable	Dependent Variables	Control Variables
VV	$Month^3$	
VV	Month	Gender
VV	Month, $Month^2$	Gender
VV	Month, $Month^2$, $Month^3$	Gender
VV	$Month^2$	Gender
VV	$Month^3$	Gender
VV	Month	CGPA
VV	Month, $Month^2$	CGPA
VV	Month, $Month^2$, $Month^3$	CGPA
VV	$Month^2$	CGPA
VV	$Month^3$	CGPA
VV	Month,	MEA
VV	Month, $Month^2$	MEA
VV	Month, $Month^2$, $Month^3$	MEA
VV	$Month^2$	MEA
VV	$Month^3$	MEA
VV	Month,	MEA, Gender, GPA
VV	Month, $Month^2$	MEA, Gender, GPA
VV	Month, $Month^2$, $Month^3$	MEA, Gender, GPA
VV	$Month^2$	MEA, Gender, GPA
VV	$Month^3$	MEA, Gender, GPA
RED	Month, SE_{RED}	
RED	Month, $Month^{2,}$ SE_{RED}	
RED	Month, $Month^2$, $Month^3$ SE_{RED}	
RED	$Month^2$ SE_{RED}	
RED	$Month^3$ SE_{RED}	
RED	Month SE_{RED}	Gender
RED	Month, $Month^2$ SE_{RED}	Gender
RED	Month, $Month^2$, $Month^3$ SE_{RED}	Gender
RED	$Month^2$ SE_{RED}	Gender
RED	$Month^3$ SE_{RED}	Gender
RED	Month SE_{RED}	CGPA

Independent Variable	Dependent Variables	Control Variables
RED	Month, $Month^2$ SE_{RED}	CGPA
RED	Month, $Month^2$, $Month^3$ SE_{RED}	CGPA
RED	$Month^2$ SE_{RED}	CGPA
RED	$Month^3$ SE_{RED}	CGPA
RED	Month, SE_{RED}	MEA
RED	Month, $Month^2$ SE_{RED}	MEA
RED	Month, $Month^2$, $Month^3$ SE_{RED}	MEA
RED	$Month^2$ SE_{RED}	MEA
RED	$Month^3$ SE_{RED}	MEA
RED	Month, SE_{RED}	MEA, Gender, GPA
RED	Month, $Month^2$ SE_{RED}	MEA, Gender, GPA
RED	Month, $Month^2$, $Month^3$ SE_{RED}	MEA, Gender, GPA
RED	$Month^2$ SE_{RED}	MEA, Gender, GPA
RED	$Month^3$ SE_{RED}	MEA, Gender, GPA
CON	Month SE_{CON}	
CON	Month, $Month^2$ SE_{CON}	
CON	Month, $Month^2$, $Month^3$ SE_{CON}	
CON	$Month^2$ SE_{CON}	
CON	$Month^3$, SE_{CON}	
CON	Month , SE_{CON}	Gender
CON	Month, $Month^2$, SE_{CON}	Gender
CON	Month, $Month^2$, $Month^3$, SE_{CON}	Gender
CON	$Month^2$, SE_{CON}	Gender
CON	$Month^3$, SE_{CON}	Gender
CON	Month , SE_{CON}	CGPA
CON	Month, $Month^2$, SE_{CON}	CGPA
CON	Month, $Month^2$, $Month^3$, SE_{CON}	CGPA
CON	$Month^2$, SE_{CON}	CGPA
CON	$Month^3$, SE_{CON}	CGPA
CON	Month, , SE_{CON}	MEA
CON	Month, $Month^2$, SE_{CON}	MEA
CON	Month, $Month^2$, $Month^3$, SE_{CON}	MEA

Independent Variable	**Dependent Variables**	**Control Variables**
CON	$Month^2$, SE_{CON}	MEA
CON	$Month^3$, SE_{CON}	MEA
CON	Month, , SE_{CON}	MEA, Gender, GPA
CON	Month, $Month^2$, SE_{CON}	MEA, Gender, GPA
CON	Month, $Month^2$, $Month^3$, SE_{CON}	MEA, Gender, GPA
CON	$Month^2$, SE_{CON}	MEA, Gender, GPA
CON	$Month^3$, SE_{CON}	MEA, Gender, GPA
CON	Month , SE_{CON}	
CON	Month, $Month^2$, SE_{CON}	
CON	Month, $Month^2$, $Month^3$, SE_{CON}	
CON	$Month^2$, SE_{CON}	
CON	$Month^3$, SE_{CON}	
CON	Month , SE_{CON}	Gender
CON	Month, $Month^2$, SE_{CON}	Gender
CON	Month, $Month^2$, $Month^3$, SE_{CON}	Gender
CON	$Month^2$, SE_{CON}	Gender
CON	$Month^3$, SE_{CON}	Gender
CON	Month , SE_{CON}	CGPA
CON	Month, $Month^2$, SE_{CON}	CGPA
CON	Month, $Month^2$, $Month^3$, SE_{CON}	CGPA
CON	$Month^2$, SE_{CON}	CGPA
CON	$Month^3$, SE_{CON}	CGPA
CON	Month, , SE_{CON}	MEA
CON	Month, $Month^2$, SE_{CON}	MEA
CON	Month, $Month^2$, $Month^3$, SE_{CON}	MEA
CON	$Month^2$, SE_{CON}	MEA
CON	$Month^3$, SE_{CON}	MEA
CON	Month, , SE_{CON}	MEA, Gender, GPA
CON	Month, $Month^2$, SE_{CON}	MEA, Gender, GPA
CON	Month, $Month^2$, $Month^3$, SE_{CON}	MEA, Gender, GPA
CON	$Month^2$, SE_{CON}	MEA, Gender, GPA
CON	$Month^3$, SE_{CON}	MEA, Gender, GPA

Independent Variable	**Dependent Variables**	**Control Variables**
EPS	Month , SE_{EPS}	
EPS	Month, $Month^2$, SE_{EPS}	
EPS	Month, $Month^2$, $Month^3$, SE_{EPS}	
EPS	$Month^2$, SE_{EPS}	
EPS	$Month^3$, SE_{EPS}	
EPS	Month , SE_{EPS}	Gender
EPS	Month, $Month^2$, SE_{EPS}	Gender
EPS	Month, $Month^2$, $Month^3$, SE_{EPS}	Gender
EPS	$Month^2$, SE_{EPS}	Gender
EPS	$Month^3$, SE_{EPS}	Gender
EPS	Month , SE_{EPS}	CGPA
EPS	Month, $Month^2$, SE_{EPS}	CGPA
EPS	Month, $Month^2$, $Month^3$, SE_{EPS}	CGPA
EPS	$Month^2$, SE_{EPS}	CGPA
EPS	$Month^3$, SE_{EPS}	CGPA
EPS	Month, SE_{EPS}	MEA
EPS	Month, $Month^2$, SE_{EPS}	MEA
EPS	Month, $Month^2$, $Month^3$, SE_{EPS}	MEA
EPS	$Month^2$, SE_{EPS}	MEA
EPS	$Month^3$, SE_{EPS}	MEA
EPS	Month, , SE_{EPS}	MEA, Gender, GPA
EPS	Month, $Month^2$, SE_{EPS}	MEA, Gender, GPA
EPS	Month, $Month^2$, $Month^3$, SE_{EPS}	MEA, Gender, GPA
EPS	$Month^2$, SE_{EPS}	MEA, Gender, GPA
EPS	$Month^3$, SE_{EPS}	MEA, Gender, GPA
CAL	Month , $SE_{IE,,}$ $SE_{PM,}$ SE_{CAL}	
CAL	Month, $Month^2$ $SE_{IE,,}$ $SE_{PM,}$ SE_{CAL}	
CAL	Month, $Month^2$, $Month^3$ $SE_{IE,,}$ $SE_{PM,}$ SE_{CAL}	
CAL	$Month^2$ $SE_{IE,,}$ $SE_{PM,}$ SE_{CAL}	
CAL	$Month^3$ $SE_{IE,,}$ $SE_{PM,}$ SE_{CAL}	
CAL	Month $SE_{IE,,}$ $SE_{PM,}$ SE_{CAL}	Gender
CAL	Month, $Month^2$ $SE_{IE,,}$ $SE_{PM,}$ SE_{CAL}	Gender

Independent Variable	**Dependent Variables**	**Control Variables**
CAL	Month, $Month^2$, $Month^3$ $SE_{IE,\,,}$ $SE_{PM,}$ SE_{CAL}	Gender
CAL	$Month^2$ $SE_{IE,\,,}$ $SE_{PM,}$ SE_{CAL}	Gender
CAL	$Month^3$ $SE_{IE,\,,}$ $SE_{PM,}$ SE_{CAL}	Gender
CAL	Month $SE_{IE,\,,}$ $SE_{PM,}$ SE_{CAL}	CGPA
CAL	Month, $Month^2$ $SE_{IE,\,,}$ $SE_{PM,}$ SE_{CAL}	CGPA
CAL	Month, $Month^2$, $Month^3$ $SE_{IE,\,,}$ $SE_{PM,}$ SE_{CAL}	CGPA
CAL	$Month^2$ $SE_{IE,\,,}$ $SE_{PM,}$ SE_{CAL}	CGPA
CAL	$Month^3$ $SE_{IE,\,,}$ $SE_{PM,}$ SE_{CAL}	CGPA
CAL	Month, $SE_{IE,\,,}$ $SE_{PM,}$ SE_{CAL}	MEA
CAL	Month, $Month^2$ $SE_{IE,\,,}$ $SE_{PM,}$ SE_{CAL}	MEA
CAL	Month, $Month^2$, $Month^3$ $SE_{IE,\,,}$ $SE_{PM,}$ SE_{CAL}	MEA
CAL	$Month^2$ $SE_{IE,\,,}$ $SE_{PM,}$ SE_{CAL}	MEA
CAL	$Month^3$ $SE_{IE,\,,}$ $SE_{PM,}$ SE_{CAL}	MEA
CAL	Month, $SE_{IE,\,,}$ $SE_{PM,}$ SE_{CAL}	MEA, Gender, GPA
CAL	Month, $Month^2$ $SE_{IE,\,,}$ $SE_{PM,}$ SE_{CAL}	MEA, Gender, GPA
CAL	Month, $Month^2$, $Month^3$ $SE_{IE,\,,}$ $SE_{PM,}$ SE_{CAL}	MEA, Gender, GPA
CAL	$Month^2$ $SE_{IE,\,,}$ $SE_{PM,}$ SE_{CAL}	MEA, Gender, GPA
CAL	$Month^3$ $SE_{IE,\,,}$ $SE_{PM,}$ SE_{CAL}	MEA, Gender, GPA
CUS	Month SE_{CAL} SE_{UV}	
CUS	Month, $Month^2$ SE_{CAL} SE_{UV}	
CUS	Month, $Month^2$, $Month^3$ SE_{CAL} SE_{UV}	
CUS	$Month^2$ SE_{CAL} SE_{UV}	
CUS	$Month^3$ SE_{CAL} SE_{UV}	
CUS	Month SE_{CAL} SE_{UV}	Gender
CUS	Month, $Month^2$ SE_{CAL} SE_{UV}	Gender
CUS	Month, $Month^2$, $Month^3$ SE_{CAL} SE_{UV}	Gender
CUS	$Month^2$ SE_{CAL} SE_{UV}	Gender
CUS	$Month^3$ SE_{CAL} SE_{UV}	Gender
CUS	Month SE_{CAL} SE_{UV}	CGPA
CUS	Month, $Month^2$ SE_{CAL} SE_{UV}	CGPA
CUS	Month, $Month^2$, $Month^3$ SE_{CAL} SE_{UV}	CGPA
CUS	$Month^2$ SE_{CAL} SE_{UV}	CGPA

Independent Variable	**Dependent Variables**	**Control Variables**
CUS	$Month^3$ SE_{CAL} SE_{UV}	CGPA
CUS	Month, SE_{CAL} SE_{UV}	MEA
CUS	Month, $Month^2$ SE_{CAL} SE_{UV}	MEA
CUS	Month, $Month^2$, $Month^3$ SE_{CAL} SE_{UV}	MEA
CUS	$Month^2$ SE_{CAL} SE_{UV}	MEA
CUS	$Month^3$ SE_{CAL} SE_{UV}	MEA
CUS	Month, SE_{CAL} SE_{UV}	MEA, Gender, GPA
CUS	Month, $Month^2$ SE_{CAL} SE_{UV}	MEA, Gender, GPA
CUS	Month, $Month^2$, $Month^3$ SE_{CAL} SE_{UV}	MEA, Gender, GPA
CUS	$Month^2$ SE_{CAL} SE_{UV}	MEA, Gender, GPA
CUS	$Month^3$ SE_{CAL} SE_{UV}	MEA, Gender, GPA
RE	Month , SE_{IE}	
RE	Month, $Month^{2,}$ SE_{IE}	
RE	Month, $Month^2$, $Month^{3,}$ SE_{IE}	
RE	$Month^2$ SE_{IE}	
RE	$Month^3$ SE_{IE}	
RE	Month SE_{IE}	Gender
RE	Month, $Month^2$ SE_{IE}	Gender
RE	Month, $Month^2$, $Month^3$ SE_{IE}	Gender
RE	$Month^2$ SE_{IE}	Gender
RE	$Month^3$ SE_{IE}	Gender
RE	Month SE_{IE}	CGPA
RE	Month, $Month^2$ SE_{IE}	CGPA
RE	Month, $Month^2$, $Month^3$ SE_{IE}	CGPA
RE	$Month^2$ SE_{IE}	CGPA
RE	$Month^3$ SE_{IE}	CGPA
RE	Month, SE_{IE}	MEA
RE	Month, $Month^2$ SE_{IE}	MEA
RE	Month, $Month^2$, $Month^3$ SE_{IE}	MEA
RE	$Month^2$ SE_{IE}	MEA
RE	$Month^3$ SE_{IE}	MEA
RE	Month, SE_{IE}	MEA, Gender, GPA

RE	Month, $Month^2$ SE_{IE}	MEA, Gender, GPA
RE	Month, $Month^2$, $Month^3$ SE_{IE}	MEA, Gender, GPA
RE	$Month^2$ SE_{IE}	MEA, Gender, GPA
RE	$Month^3$ SE_{IE}	MEA, Gender, GPA
VV	Month SE_{UV}	
VV	Month, $Month^2$ SE_{UV}	
VV	Month, $Month^2$, $Month^3$ SE_{UV}	
VV	$Month^2$ SE_{UV}	
VV	$Month^3$ SE_{UV}	
VV	Month SE_{UV}	Gender
VV	Month, $Month^2$ SE_{UV}	Gender
VV	Month, $Month^2$, $Month^3$ SE_{UV}	Gender
VV	$Month^2$ SE_{UV}	Gender
VV	$Month^3$ SE_{UV}	Gender
VV	Month SE_{UV}	CGPA
VV	Month, $Month^2$ SE_{UV}	CGPA
VV	Month, $Month^2$, $Month^3$ SE_{UV}	CGPA
VV	$Month^2$ SE_{UV}	CGPA
VV	$Month^3$ SE_{UV}	CGPA
VV	Month, SE_{UV}	MEA
VV	Month, $Month^2$ SE_{UV}	MEA
VV	Month, $Month^2$, $Month^3$ SE_{UV}	MEA
VV	$Month^2$ SE_{UV}	MEA
VV	$Month^3$ SE_{UV}	MEA
VV	Month, SE_{UV}	MEA, Gender, GPA
VV	Month, $Month^2$ SE_{UV}	MEA, Gender, GPA
VV	Month, $Month^2$, $Month^3$ SE_{UV}	MEA, Gender, GPA
VV	$Month^2$ SE_{UV}	MEA, Gender, GPA
VV	$Month^3$ SE_{UV}	MEA, Gender, GPA
RED	Month Quick Learning Omniscient Authority Simple Knowledge Certain Knowledge Fixed Ability	

Independent Variable	**Dependent Variables**	**Control Variables**
RED	Month, Month^2 Quick Learning Omniscient Authority Simple Knowledge Certain Knowledge Fixed Ability	
RED	Month, Month^2, Month^3 Quick Learning Omniscient Authority Simple Knowledge Certain Knowledge Fixed Ability	
RED	Month^2 Quick Learning Omniscient Authority Simple Knowledge Certain Knowledge Fixed Ability	
RED	Month^3 Quick Learning Omniscient Authority Simple Knowledge Certain Knowledge Fixed Ability	
RED	Month Quick Learning Omniscient Authority Simple Knowledge Certain Knowledge Fixed Ability	Gender
RED	Month, Month^2 Quick Learning Omniscient Authority Simple Knowledge Certain Knowledge Fixed Ability	Gender
RED	Month, Month^2, Month^3 Quick Learning Omniscient Authority Simple Knowledge Certain Knowledge Fixed Ability	Gender
RED	Month^2 Quick Learning Omniscient Authority Simple Knowledge Certain Knowledge Fixed Ability	Gender
RED	Month^3 Quick Learning Omniscient Authority Simple Knowledge Certain Knowledge Fixed Ability	Gender
RED	Month Quick Learning Omniscient Authority Simple Knowledge Certain Knowledge Fixed Ability	CGPA

Independent Variable	Dependent Variables	Control Variables
RED	Month, $Month^2$ Quick Learning Omniscient Authority Simple Knowledge Certain Knowledge Fixed Ability	CGPA
RED	Month, $Month^2$, $Month^3$ Quick Learning Omniscient Authority Simple Knowledge Certain Knowledge Fixed Ability	CGPA
RED	$Month^2$ Quick Learning Omniscient Authority Simple Knowledge Certain Knowledge Fixed Ability	CGPA
RED	$Month^3$ Quick Learning Omniscient Authority Simple Knowledge Certain Knowledge Fixed Ability	CGPA
RED	Month, Quick Learning Omniscient Authority Simple Knowledge Certain Knowledge Fixed Ability	MEA
RED	Month, $Month^2$ Quick Learning Omniscient Authority Simple Knowledge Certain Knowledge Fixed Ability	MEA
RED	Month, $Month^2$, $Month^3$ Quick Learning Omniscient Authority Simple Knowledge Certain Knowledge Fixed Ability	MEA
RED	$Month^2$ Quick Learning Omniscient Authority Simple Knowledge Certain Knowledge Fixed Ability	MEA
RED	$Month^3$ Quick Learning Omniscient Authority Simple Knowledge Certain Knowledge Fixed Ability	MEA
RED	Month, Quick Learning Omniscient Authority Simple Knowledge Certain Knowledge Fixed Ability	MEA, Gender, GPA
RED	Month, $Month^2$ Quick Learning Omniscient Authority, Simple Knowledge Certain Knowledge, Fixed Ability	MEA, Gender, GPA

Independent Variable	Dependent Variables	Control Variables
RED	Month, Month^2, Month^3 Quick Learning Omniscient Authority Simple Knowledge Certain Knowledge Fixed Ability	MEA, Gender, GPA
RED	Month^2 Quick Learning Omniscient Authority Simple Knowledge Certain Knowledge Fixed Ability	MEA, Gender, GPA
RED	Month^3 Quick Learning Omniscient Authority Simple Knowledge Certain Knowledge Fixed Ability	MEA, Gender, GPA
CON	Month Quick Learning Omniscient Authority Simple Knowledge Certain Knowledge Fixed Ability	
CON	Month, Month^2 Quick Learning Omniscient Authority Simple Knowledge Certain Knowledge Fixed Ability	
CON	Month, Month^2, Month^3 , Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	
CON	Month^2, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	
CON	Month^3, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	
CON	Month , Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	Gender
CON	Month, Month^2, Quick Learning, Omniscient Authority, Simple Knowledge,Certain Knowledge, Fixed Ability	Gender
CON	Month, Month^2, Month^3 , Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	Gender

Independent Variable	**Dependent Variables**	**Control Variables**
CON	$Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	Gender
CON	$Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	Gender
CON	Month , Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	CGPA
CON	Month, $Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	CGPA
CON	Month, $Month^2$, $Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	CGPA
CON	$Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	CGPA
CON	$Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	CGPA
CON	Month, , Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA
CON	Month, $Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA
CON	Month, $Month^2$, $Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA
CON	$Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA

Independent Variable	**Dependent Variables**	**Control Variables**
CON	$Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA
CON	Month, , Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA, Gender, GPA
CON	Month, $Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA, Gender, GPA
CON	Month, $Month^2$, $Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA, Gender, GPA
CON	$Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA, Gender, GPA
CON	$Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA, Gender, GPA
CON	Month , Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	
CON	Month, $Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	
CON	Month, $Month^2$, $Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	
CON	$Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	
CON	$Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	

Independent Variable	**Dependent Variables**	**Control Variables**
CON	Month , Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	Gender
CON	Month, $Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	Gender
CON	Month, $Month^2$, $Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	Gender
CON	$Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	Gender
CON	$Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	Gender
CON	Month , Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	CGPA
CON	Month, $Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	CGPA
CON	Month, $Month^2$, $Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	CGPA
CON	$Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	CGPA
CON	$Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	CGPA
CON	Month, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA

Independent Variable	Dependent Variables	Control Variables
CON	Month, $Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA
CON	Month, $Month^2$, $Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA
CON	$Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA
CON	$Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA
CON	Month, , Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA, Gender, GPA
CON	Month, $Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA, Gender, GPA
CON	Month, $Month^2$, $Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA, Gender, GPA
CON	$Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA, Gender, GPA
CON	$Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA, Gender, GPA
EPS	Month , Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	
EPS	Month, $Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	

Independent Variable	**Dependent Variables**	**Control Variables**
EPS	Month, $Month^2$, $Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	
EPS	$Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	
EPS	$Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	
EPS	Month , Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	Gender
EPS	Month, $Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	Gender
EPS	Month, $Month^2$, $Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	Gender
EPS	$Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	Gender
EPS	$Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	Gender
EPS	Month , Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	CGPA
EPS	Month, $Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	CGPA
EPS	Month, $Month^2$, $Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge, Certain Knowledge, Fixed Ability	CGPA

Independent Variable	Dependent Variables	Control Variables
EPS	$Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	CGPA
EPS	$Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	CGPA
EPS	Month, , Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA
EPS	Month, $Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA
EPS	Month, $Month^2$, $Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA
EPS	$Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA
EPS	$Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA
EPS	Month, , Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA, Gender, GPA
EPS	Month, $Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA, Gender, GPA
EPS	Month, $Month^2$, $Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge, Certain Knowledge, Fixed Ability	MEA, Gender, GPA
EPS	$Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA, Gender, GPA

Independent Variable	Dependent Variables	Control Variables
EPS	$Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA, Gender, GPA
CAL	Month , Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	
CAL	Month, $Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	
CAL	Month, $Month^2$, $Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	
CAL	$Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	
CAL	$Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	
CAL	Month , Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	Gender
CAL	Month, $Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	Gender
CAL	Month, $Month^2$, $Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	Gender
CAL	$Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	Gender

Independent Variable	Dependent Variables	Control Variables
CAL	$Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	Gender
CAL	Month , Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	CGPA
CAL	Month, $Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	CGPA
CAL	Month, $Month^2$, $Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	CGPA
CAL	$Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	CGPA
CAL	$Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	CGPA
CAL	Month, , Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA
CAL	Month, $Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA
CAL	Month, $Month^2$, $Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA
CAL	$Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA
CAL	$Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA

Independent Variable	**Dependent Variables**	**Control Variables**
CAL	Month, , Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA, Gender, GPA
CAL	Month, $Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA, Gender, GPA
CAL	Month, $Month^2$, $Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA, Gender, GPA
CAL	$Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA, Gender, GPA
CAL	$Month^3$, , Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA, Gender, GPA
CUS	Month , Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	
CUS	Month, $Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	
CUS	Month, $Month^2$, $Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	
CUS	$Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	
CUS	$Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	
CUS	Month , Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	Gender

Independent Variable	Dependent Variables	Control Variables
CUS	Month, $Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	Gender
CUS	Month, $Month^2$, $Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	Gender
CUS	$Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	Gender
CUS	$Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	Gender
CUS	Month , Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	CGPA
CUS	Month, $Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	CGPA
CUS	Month, $Month^2$, $Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	CGPA
CUS	$Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	CGPA
CUS	$Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	CGPA
CUS	Month, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA
CUS	Month, $Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge, Certain Knowledge, Fixed Ability	MEA

Independent Variable	Dependent Variables	Control Variables
CUS	Month, $Month^2$, $Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA
CUS	$Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA
CUS	$Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA
CUS	Month, , Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA, Gender, GPA
CUS	Month, $Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA, Gender, GPA
CUS	Month, $Month^2$, $Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA, Gender, GPA
CUS	$Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA, Gender, GPA
CUS	$Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA, Gender, GPA
RE	Month , Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	
RE	Month, $Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge, Certain Knowledge, Fixed Ability	
RE	Month, $Month^2$, $Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge, Certain Knowledge, Fixed Ability	

Independent Variable	**Dependent Variables**	**Control Variables**
RE	$Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	
RE	$Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	
RE	Month , Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	Gender
RE	Month, $Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	Gender
RE	Month, $Month^2$, $Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	Gender
RE	$Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	Gender
RE	$Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	Gender
RE	Month , Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	CGPA
RE	Month, $Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	CGPA
RE	Month, $Month^2$, $Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	CGPA
RE	$Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	CGPA

Independent Variable	Dependent Variables	Control Variables
RE	$Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	CGPA
RE	Month, , Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA
RE	Month, $Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA
RE	Month, $Month^2$, $Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA
RE	$Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA
RE	$Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA
RE	Month, , Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA, Gender, GPA
RE	Month, $Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA, Gender, GPA
RE	Month, $Month^2$, $Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA, Gender, GPA
RE	$Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA, Gender, GPA
RE	$Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA, Gender, GPA

Independent Variable	Dependent Variables	Control Variables
VV	Month , Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	
VV	Month, Month^2, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	
VV	Month, Month^2, Month^3, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	
VV	Month^2, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	
VV	Month^3, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	
VV	Month , Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	Gender
VV	Month, Month^2 , Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	Gender
VV	Month, Month^2, Month^3 , Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	Gender
VV	Month^2, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	Gender
VV	Month^3, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	Gender
VV	Month , Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	CGPA

Independent Variable	Dependent Variables	Control Variables
VV	Month, $Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	CGPA
VV	Month, $Month^2$, $Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	CGPA
VV	$Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	CGPA
VV	$Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	CGPA
VV	Month, , Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA
VV	Month, $Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA
VV	Month, $Month^2$, $Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA
VV	$Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA
VV	$Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA
VV	Month, , Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA, Gender, GPA
VV	Month, $Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA, Gender, GPA

Independent Variable	**Dependent Variables**	**Control Variables**
VV	Month, $Month^2$, $Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA, Gender, GPA
VV	$Month^2$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA, Gender, GPA
VV	$Month^3$, Quick Learning, Omniscient Authority, Simple Knowledge ,Certain Knowledge, Fixed Ability	MEA, Gender, GPA
RED	Month , Awareness	
RED	Month, $Month^2$, Awareness	
RED	Month, $Month^2$, $Month^3$, Awareness	
RED	$Month^2$, Awareness	
RED	$Month^3$, Awareness	
RED	Month , Awareness	Gender
RED	Month, $Month^2$, Awareness	Gender
RED	Month, $Month^2$, $Month^3$, Awareness	Gender
RED	$Month^2$, Awareness	Gender
RED	$Month^3$, Awareness	Gender
RED	Month , Awareness	CGPA
RED	Month, $Month^2$, Awareness	CGPA
RED	Month, $Month^2$, $Month^{3,}$, Awareness	CGPA
RED	$Month^{2,}$, Awareness	CGPA
RED	$Month^{3,}$, Awareness	CGPA
RED	Month, , Awareness	MEA
RED	Month, $Month^2$, Awareness	MEA
RED	Month, $Month^2$, $Month^3$, Awareness	MEA
RED	$Month^2$, Awareness	MEA
RED	$Month^3$, Awareness	MEA
RED	Month, , Awareness	MEA, Gender, GPA
RED	Month, $Month^2$, Awareness	MEA, Gender, GPA
RED	Month, $Month^2$, $Month^3$, Awareness	MEA, Gender, GPA

Independent Variable	Dependent Variables	Control Variables
RED	$Month^2$, Awareness	MEA, Gender, GPA
RED	$Month^3$, Awareness	MEA, Gender, GPA
CON	Month , Awareness	
CON	Month, $Month^2$, Awareness	
CON	Month, $Month^2$, $Month^3$, Awareness	
CON	$Month^2$, Awareness	
CON	$Month^3$, Awareness	
CON	Month , Awareness	Gender
CON	Month, $Month^2$, Awareness	Gender
CON	Month, $Month^2$, $Month^3$, Awareness	Gender
CON	$Month^2$, Awareness	Gender
CON	$Month^3$, Awareness	Gender
CON	Month , Awareness	CGPA
CON	Month, $Month^2$, Awareness	CGPA
CON	Month, $Month^2$, $Month^3$, Awareness	CGPA
CON	$Month^2$, Awareness	CGPA
CON	$Month^3$, Awareness	CGPA
CON	Month, , Awareness	MEA
CON	Month, $Month^2$, Awareness	MEA
CON	Month, $Month^2$, $Month^3$, Awareness	MEA
CON	$Month^2$, Awareness	MEA
CON	$Month^3$, Awareness	MEA
CON	Month, , Awareness	MEA, Gender, GPA
CON	Month, $Month^{2,}$, Awareness	MEA, Gender, GPA
CON	Month, $Month^2$, $Month^3$, Awareness	MEA, Gender, GPA
CON	$Month^2$, Awareness	MEA, Gender, GPA
CON	$Month^3$, Awareness	MEA, Gender, GPA
CON	Month , Awareness	
CON	Month, $Month^2$, Awareness	
CON	Month, $Month^2$, $Month^3$, Awareness	
CON	$Month^2$, Awareness	
CON	$Month^3$, Awareness	

Independent Variable	Dependent Variables	Control Variables
CON	Month , Awareness	Gender
CON	Month, $Month^2$, Awareness	Gender
CON	Month, $Month^2$, $Month^3$, Awareness	Gender
CON	$Month^2$, Awareness	Gender
CON	$Month^3$, Awareness	Gender
CON	Month , Awareness	CGPA
CON	Month, $Month^2$, Awareness	CGPA
CON	Month, $Month^2$, $Month^3$, Awareness	CGPA
CON	$Month^2$, Awareness	CGPA
CON	$Month^3$, Awareness	CGPA
CON	Month, Awareness	MEA
CON	Month, $Month^2$, Awareness	MEA
CON	Month, $Month^2$, $Month^3$, Awareness	MEA
CON	$Month^2$, Awareness	MEA
CON	$Month^3$, Awareness	MEA
CON	Month, , Awareness	MEA, Gender, GPA
CON	Month, $Month^2$, Awareness	MEA, Gender, GPA
CON	Month, $Month^2$, $Month^3$, Awareness	MEA, Gender, GPA
CON	$Month^2$, Awareness	MEA, Gender, GPA
CON	$Month^3$, Awareness	MEA, Gender, GPA
EPS	Month , Awareness	
EPS	Month, $Month^2$, Awareness	
EPS	Month, $Month^2$, $Month^3$, Awareness	
EPS	$Month^2$, Awareness	
EPS	$Month^3$, Awareness	
EPS	Month , Awareness	Gender
EPS	Month, $Month^2$, Awareness	Gender
EPS	Month, $Month^2$, $Month^3$, Awareness	Gender
EPS	$Month^2$, Awareness	Gender
EPS	$Month^3$, Awareness	Gender
EPS	Month , Awareness	CGPA
EPS	Month, $Month^2$, Awareness	CGPA

Independent Variable	**Dependent Variables**	**Control Variables**
EPS	Month, $Month^2$, $Month^3$, Awareness	CGPA
EPS	$Month^2$, Awareness	CGPA
EPS	$Month^3$, Awareness	CGPA
EPS	Month, Awareness	MEA
EPS	Month, $Month^2$, Awareness	MEA
EPS	Month, $Month^2$, $Month^3$, Awareness	MEA
EPS	$Month^2$, Awareness	MEA
EPS	$Month^3$, Awareness	MEA
EPS	Month, Awareness	MEA, Gender, GPA
EPS	Month, $Month^2$, Awareness	MEA, Gender, GPA
EPS	Month, $Month^2$, $Month^3$, Awareness	MEA, Gender, GPA
EPS	$Month^2$, Awareness	MEA, Gender, GPA
EPS	$Month^3$, Awareness	MEA, Gender, GPA
CAL	Month , Awareness	
CAL	Month, $Month^2$, Awareness	
CAL	Month, $Month^2$, $Month^3$, Awareness	
CAL	$Month^2$, Awareness	
CAL	$Month^3$, Awareness	
CAL	Month , Awareness	Gender
CAL	Month, $Month^2$, Awareness	Gender
CAL	Month, $Month^2$, $Month^3$, Awareness	Gender
CAL	$Month^2$, Awareness	Gender
CAL	$Month^3$, Awareness	Gender
CAL	Month , Awareness	CGPA
CAL	Month, $Month^2$, Awareness	CGPA
CAL	Month, $Month^2$, $Month^3$, Awareness	CGPA
CAL	$Month^2$, Awareness	CGPA
CAL	$Month^3$, Awareness	CGPA
CAL	Month, Awareness	MEA
CAL	Month, $Month^2$, Awareness	MEA
CAL	Month, $Month^2$, $Month^3$, Awareness	MEA
CAL	$Month^2$, Awareness	MEA

Independent Variable	Dependent Variables	Control Variables
CAL	$Month^3$, Awareness	MEA
CAL	Month, , Awareness	MEA, Gender, GPA
CAL	Month, $Month^2$, Awareness	MEA, Gender, GPA
CAL	Month, $Month^2$, $Month^3$, Awareness	MEA, Gender, GPA
CAL	$Month^2$, Awareness	MEA, Gender, GPA
CAL	$Month^3$, Awareness	MEA, Gender, GPA
CUS	Month , Awareness	
CUS	Month, $Month^2$, Awareness	
CUS	Month, $Month^2$, $Month^3$, Awareness	
CUS	$Month^2$, Awareness	
CUS	$Month^3$, Awareness	
CUS	Month , Awareness	Gender
CUS	Month, $Month^2$, Awareness	Gender
CUS	Month, $Month^2$, $Month^3$, Awareness	Gender
CUS	$Month^2$, Awareness	Gender
CUS	$Month^3$, Awareness	Gender
CUS	Month , Awareness	CGPA
CUS	Month, $Month^2$, Awareness	CGPA
CUS	Month, $Month^2$, $Month^3$, Awareness	CGPA
CUS	$Month^2$, Awareness	CGPA
CUS	$Month^3$, Awareness	CGPA
CUS	Month, Awareness	MEA
CUS	Month, $Month^2$, Awareness	MEA
CUS	Month, $Month^2$, $Month^3$, Awareness	MEA
CUS	$Month^2$, Awareness	MEA
CUS	$Month^3$, Awareness	MEA
CUS	Month, , Awareness	MEA, Gender, GPA
CUS	Month, $Month^2$, Awareness	MEA, Gender, GPA
CUS	Month, $Month^2$, $Month^3$, Awareness	MEA, Gender, GPA
CUS	$Month^2$, Awareness	MEA, Gender, GPA
CUS	$Month^3$, Awareness	MEA, Gender, GPA
RE	Month , Awareness	

Independent Variable	**Dependent Variables**	**Control Variables**
RE	Month, $Month^2$, Awareness	
RE	Month, $Month^2$, $Month^3$, Awareness	
RE	$Month^2$, Awareness	
RE	$Month^3$, Awareness	
RE	Month , Awareness	Gender
RE	Month, $Month^2$, Awareness	Gender
RE	Month, $Month^2$, $Month^3$, Awareness	Gender
RE	$Month^2$, Awareness	Gender
RE	$Month^3$, Awareness	Gender
RE	Month , Awareness	CGPA
RE	Month, $Month^2$, Awareness	CGPA
RE	Month, $Month^2$, $Month^3$, Awareness	CGPA
RE	$Month^2$, Awareness	CGPA
RE	$Month^3$, Awareness	CGPA
RE	Month, Awareness	MEA
RE	Month, $Month^2$, Awareness	MEA
RE	Month, $Month^2$, $Month^3$, Awareness	MEA
RE	$Month^2$, Awareness	MEA
RE	$Month^3$, Awareness	MEA
RE	Month, , Awareness	MEA, Gender, GPA
RE	Month, $Month^2$, Awareness	MEA, Gender, GPA
RE	Month, $Month^2$, $Month^3$, Awareness	MEA, Gender, GPA
RE	$Month^2$, Awareness	MEA, Gender, GPA
RE	$Month^3$, Awareness	MEA, Gender, GPA
VV	Month , Awareness	
VV	Month, $Month^2$, Awareness	
VV	Month, $Month^2$, $Month^3$, Awareness	
VV	$Month^2$, Awareness	
VV	$Month^3$, Awareness	
VV	Month , Awareness	Gender
VV	Month, $Month^2$, Awareness	Gender
VV	Month, $Month^2$, $Month^3$, Awareness	Gender

Independent Variable	Dependent Variables	Control Variables
VV	$Month^2$, Awareness	Gender
VV	$Month^3$, Awareness	Gender
VV	Month , Awareness	CGPA
VV	Month, $Month^2$, Awareness	CGPA
VV	Month, $Month^2$, $Month^3$, Awareness	CGPA
VV	$Month^2$, Awareness	CGPA
VV	$Month^3$, Awareness	CGPA
VV	Month, Awareness	MEA
VV	Month, $Month^2$, Awareness	MEA
VV	Month, $Month^2$, $Month^3$, Awareness	MEA
VV	$Month^2$, Awareness	MEA
VV	$Month^3$, Awareness	MEA
VV	Month, , Awareness	MEA, Gender, GPA
VV	Month, $Month^2$, Awareness	MEA, Gender, GPA
VV	Month, $Month^2$, $Month^3$, Awareness	MEA, Gender, GPA
VV	$Month^2$, Awareness	MEA, Gender, GPA
VV	$Month^3$, Awareness	MEA, Gender, GPA
RED	Month , Self-checking	
RED	Month, $Month^2$, Self-checking	
RED	Month, $Month^2$, $Month^3$, Self-checking	
RED	$Month^2$, Self-checking	
RED	$Month^3$, Self-checking	
RED	Month , Self-checking	Gender
RED	Month, $Month^2$, Self-checking	Gender
RED	Month, $Month^2$, $Month^3$, Self-checking	Gender
RED	$Month^2$, Self-checking	Gender
RED	$Month^3$, Self-checking	Gender
RED	Month , Self-checking	CGPA
RED	Month, $Month^2$, Self-checking	CGPA
RED	Month, $Month^2$, $Month^3$, Self-checking	CGPA
RED	$Month^2$, Self-checking	CGPA

Independent Variable	**Dependent Variables**	**Control Variables**
RED	$Month^3$, Self-checking	CGPA
RED	Month , Self-checking	MEA
RED	Month, $Month^2$, Self-checking	MEA
RED	Month, $Month^2$, $Month^3$, Self-checking	MEA
RED	$Month^2$, Self-checking	MEA
RED	$Month^3$, Self-checking	MEA
RED	Month , Self-checking	MEA, Gender, GPA
RED	Month, $Month^2$, Self-checking	MEA, Gender, GPA
RED	Month, $Month^2$, $Month^3$, Self-checking	MEA, Gender, GPA
RED	$Month^2$, Self-checking	MEA, Gender, GPA
RED	$Month^3$, Self-checking	MEA, Gender, GPA
CON	Month , Self-checking	
CON	Month, $Month^2$, Self-checking	
CON	Month, $Month^2$, $Month^3$, Self-checking	
CON	$Month^2$, Self-checking	
CON	$Month^3$, Self-checking	
CON	Month , Self-checking	Gender
CON	Month, $Month^2$, Self-checking	Gender
CON	Month, $Month^2$, $Month^3$, Self-checking	Gender
CON	$Month^2$, Self-checking	Gender
CON	$Month^3$, Self-checking	Gender
CON	Month , Self-checking	CGPA
CON	Month, $Month^2$, Self-checking	CGPA
CON	Month, $Month^2$, $Month^3$, Self-checking	CGPA
CON	$Month^2$, Self-checking	CGPA
CON	$Month^3$, Self-checking	CGPA
CON	Month , Self-checking	MEA
CON	Month, $Month^2$, Self-checking	MEA
CON	Month, $Month^2$, $Month^3$, Self-checking	MEA
CON	$Month^2$, Self-checking	MEA
CON	$Month^3$, Self-checking	MEA

Independent Variable	**Dependent Variables**	**Control Variables**
CON	Month, Month^2 , Self-checking	MEA, Gender, GPA
CON	Month, Month^2, Month^3, Self-checking	MEA, Gender, GPA
CON	Month^2, Self-checking	MEA, Gender, GPA
CON	Month^3, Self-checking	MEA, Gender, GPA
CON	Month , Self-checking	
CON	Month, Month^2 , Self-checking	
CON	Month, Month^2, Month^3, Self-checking	
CON	Month^2, Self-checking	
CON	Month^3, Self-checking	
CON	Month , Self-checking	Gender
CON	Month, Month^2 , Self-checking	Gender
CON	Month, Month^2, Month^3, Self-checking	Gender
CON	Month^2, Self-checking	Gender
CON	Month^3, Self-checking	Gender
CON	Month , Self-checking	CGPA
CON	Month, Month^2 , Self-checking	CGPA
CON	Month, Month^2, Month^3, Self-checking	CGPA
CON	Month^2, Self-checking	CGPA
CON	Month^3, Self-checking	CGPA
CON	Month , Self-checking	MEA
CON	Month, Month^2 , Self-checking	MEA
CON	Month, Month^2, Month^3, Self-checking	MEA
CON	Month^2, Self-checking	MEA
CON	Month^3, Self-checking	MEA
CON	Month , Self-checking	MEA, Gender, GPA
CON	Month, Month^2 , Self-checking	MEA, Gender, GPA
CON	Month, Month^2, Month^3, Self-checking	MEA, Gender, GPA
CON	Month^2, Self-checking	MEA, Gender, GPA
CON	Month^3, Self-checking	MEA, Gender, GPA
EPS	Month , Self-checking	
EPS	Month, Month^2 , Self-checking	

Independent Variable	**Dependent Variables**	**Control Variables**
EPS	Month, $Month^2$, $Month^3$, Self-checking	
EPS	$Month^2$, Self-checking	
EPS	$Month^3$, Self-checking	
EPS	Month , Self-checking	Gender
EPS	Month, $Month^2$, Self-checking	Gender
EPS	Month, $Month^2$, $Month^3$, Self-checking	Gender
EPS	$Month^2$, Self-checking	Gender
EPS	$Month^3$, Self-checking	Gender
EPS	Month , Self-checking	CGPA
EPS	Month, $Month^2$, Self-checking	CGPA
EPS	Month, $Month^2$, $Month^3$, Self-checking	CGPA
EPS	$Month^2$, Self-checking	CGPA
EPS	$Month^3$, Self-checking	CGPA
EPS	Month , Self-checking	MEA
EPS	Month, $Month^2$, Self-checking	MEA
EPS	Month, $Month^2$, $Month^3$, Self-checking	MEA
EPS	$Month^2$, Self-checking	MEA
EPS	$Month^3$, Self-checking	MEA
EPS	Month , Self-checking	MEA, Gender, GPA
EPS	Month, $Month^2$, Self-checking	MEA, Gender, GPA
EPS	Month, $Month^2$, $Month^3$, Self-checking	MEA, Gender, GPA
EPS	$Month^2$, Self-checking	MEA, Gender, GPA
EPS	$Month^3$, Self-checking	MEA, Gender, GPA
CAL	Month , Self-checking	
CAL	Month, $Month^2$, Self-checking	
CAL	Month, $Month^2$, $Month^3$, Self-checking	
CAL	$Month^2$, Self-checking	
CAL	$Month^3$, Self-checking	
CAL	Month , Self-checking	Gender
CAL	Month, $Month^2$, Self-checking	Gender
CAL	Month, $Month^2$, $Month^3$, Self-checking	Gender

Independent Variable	Dependent Variables	Control Variables
CAL	$Month^2$, Self-checking	Gender
CAL	$Month^3$, Self-checking	Gender
CAL	Month , Self-checking	CGPA
CAL	Month, $Month^2$, Self-checking	CGPA
CAL	Month, $Month^2$, $Month^3$, Self-checking	CGPA
CAL	$Month^2$, Self-checking	CGPA
CAL	$Month^3$, Self-checking	CGPA
CAL	Month , Self-checking	MEA
CAL	Month, $Month^2$, Self-checking	MEA
CAL	Month, $Month^2$, $Month^3$, Self-checking	MEA
CAL	$Month^2$, Self-checking	MEA
CAL	$Month^3$, Self-checking	MEA
CAL	Month , Self-checking	MEA, Gender, GPA
CAL	Month, $Month^2$, Self-checking	MEA, Gender, GPA
CAL	Month, $Month^2$, $Month^3$, Self-checking	MEA, Gender, GPA
CAL	$Month^2$, Self-checking	MEA, Gender, GPA
CAL	$Month^3$, Self-checking	MEA, Gender, GPA
CUS	Month , Self-checking	
CUS	Month, $Month^2$, Self-checking	
CUS	Month, $Month^2$, $Month^3$, Self-checking	
CUS	$Month^2$, Self-checking	
CUS	$Month^3$, Self-checking	
CUS	Month , Self-checking	Gender
CUS	Month, $Month^2$, Self-checking	Gender
CUS	Month, $Month^2$, $Month^3$, Self-checking	Gender
CUS	$Month^2$, Self-checking	Gender
CUS	$Month^3$, Self-checking	Gender
CUS	Month , Self-checking	CGPA
CUS	Month, $Month^2$, Self-checking	CGPA
CUS	Month, $Month^2$, $Month^3$, Self-checking	CGPA
CUS	$Month^2$, Self-checking	CGPA

Independent Variable	**Dependent Variables**	**Control Variables**
CUS	$Month^3$, Self-checking	CGPA
CUS	Month , Self-checking	MEA
CUS	Month, $Month^2$, Self-checking	MEA
CUS	Month, $Month^2$, $Month^3$, Self-checking	MEA
CUS	$Month^2$, Self-checking	MEA
CUS	$Month^3$, Self-checking	MEA
CUS	Month , Self-checking	MEA, Gender, GPA
CUS	Month, $Month^2$, Self-checking	MEA, Gender, GPA
CUS	Month, $Month^2$, $Month^3$, Self-checking	MEA, Gender, GPA
CUS	$Month^2$, Self-checking	MEA, Gender, GPA
CUS	$Month^3$, Self-checking	MEA, Gender, GPA
RE	Month , Self-checking	
RE	Month, $Month^2$, Self-checking	
RE	Month, $Month^2$, $Month^3$, Self-checking	
RE	$Month^2$, Self-checking	
RE	$Month^3$, Self-checking	
RE	Month , Self-checking	Gender
RE	Month, $Month^2$, Self-checking	Gender
RE	Month, $Month^2$, $Month^3$, Self-checking	Gender
RE	$Month^2$, Self-checking	Gender
RE	$Month^3$, Self-checking	Gender
RE	Month , Self-checking	CGPA
RE	Month, $Month^2$, Self-checking	CGPA
RE	Month, $Month^2$, $Month^3$, Self-checking	CGPA
RE	$Month^2$, Self-checking	CGPA
RE	$Month^3$, Self-checking	CGPA
RE	Month , Self-checking	MEA
RE	Month, $Month^2$, Self-checking	MEA
RE	Month, $Month^2$, $Month^3$, Self-checking	MEA
RE	$Month^2$, Self-checking	MEA
RE	$Month^3$, Self-checking	MEA

Independent Variable	**Dependent Variables**	**Control Variables**
RE	Month , Self-checking	MEA, Gender, GPA
RE	Month, $Month^2$, Self-checking	MEA, Gender, GPA
RE	Month, $Month^2$, $Month^3$, Self-checking	MEA, Gender, GPA
RE	$Month^2$, Self-checking	MEA, Gender, GPA
RE	$Month^3$, Self-checking	MEA, Gender, GPA
VV	Month , Self-checking	
VV	Month, $Month^2$, Self-checking	
VV	Month, $Month^2$, $Month^3$, Self-checking	
VV	$Month^2$, Self-checking	
VV	$Month^3$, Self-checking	
VV	Month , Self-checking	Gender
VV	Month, $Month^2$, Self-checking	Gender
VV	Month, $Month^2$, $Month^3$, Self-checking	Gender
VV	$Month^2$, Self-checking	Gender
VV	$Month^3$, Self-checking	Gender
VV	Month , Self-checking	CGPA
VV	Month, $Month^2$, Self-checking	CGPA
VV	Month, $Month^2$, $Month^3$, Self-checking	CGPA
VV	$Month^2$, Self-checking	CGPA
VV	$Month^3$, Self-checking	CGPA
VV	Month , Self-checking	MEA
VV	Month, $Month^2$, Self-checking	MEA
VV	Month, $Month^2$, $Month^3$, Self-checking	MEA
VV	$Month^2$, Self-checking	MEA
VV	$Month^3$, Self-checking	MEA
VV	Month , Self-checking	MEA, Gender, GPA
VV	Month, $Month^2$, Self-checking	MEA, Gender, GPA
VV	Month, $Month^2$, $Month^3$, Self-checking	MEA, Gender, GPA
VV	$Month^2$, Self-checking	MEA, Gender, GPA
VV	$Month^3$, Self-checking	MEA, Gender, GPA
RED	$Month^2$, Cognitive Strategy	

Independent Variable	**Dependent Variables**	**Control Variables**
RED	$Month^3$, Cognitive Strategy	
RED	Month , Cognitive Strategy	Gender
RED	Month, $Month^2$, Cognitive Strategy	Gender
RED	Month, $Month^2$, $Month^3$, Cognitive Strategy	Gender
RED	$Month^2$, Cognitive Strategy	Gender
RED	$Month^3$, Cognitive Strategy	Gender
RED	Month , Cognitive Strategy	CGPA
RED	Month, $Month^2$, Cognitive Strategy	CGPA
RED	Month, $Month^2$, $Month^3$, Cognitive Strategy	CGPA
RED	$Month^2$, Cognitive Strategy	CGPA
RED	$Month^3$, Cognitive Strategy	CGPA
RED	Month , Cognitive Strategy	MEA
RED	Month, $Month^2$, Cognitive Strategy	MEA
RED	Month, $Month^2$, $Month^3$, Cognitive Strategy	MEA
RED	$Month^2$, Cognitive Strategy	MEA
RED	$Month^3$, Cognitive Strategy	MEA
RED	Month , Cognitive Strategy	MEA, Gender, GPA
RED	Month, $Month^2$, Cognitive Strategy	MEA, Gender, GPA
RED	Month, $Month^2$, $Month^3$, Cognitive Strategy	MEA, Gender, GPA
RED	$Month^2$, Cognitive Strategy	MEA, Gender, GPA
RED	$Month^3$, Cognitive Strategy	MEA, Gender, GPA
CON	Month , Cognitive Strategy	
CON	Month, $Month^2$, Cognitive Strategy	
CON	Month, $Month^2$, $Month^3$, Cognitive Strategy	
CON	$Month^2$, Cognitive Strategy	
CON	$Month^3$, Cognitive Strategy	
CON	Month , Cognitive Strategy	Gender
CON	Month, $Month^2$, Cognitive Strategy	Gender
CON	Month, $Month^2$, $Month^3$, Cognitive Strategy	Gender
CON	$Month^2$, Cognitive Strategy	Gender
CON	$Month^3$, Cognitive Strategy	Gender

Independent Variable	Dependent Variables	Control Variables
CON	Month , Cognitive Strategy	CGPA
CON	Month, $Month^2$, Cognitive Strategy	CGPA
CON	Month, $Month^2$, $Month^3$, Cognitive Strategy	CGPA
CON	$Month^2$, Cognitive Strategy	CGPA
CON	$Month^3$, Cognitive Strategy	CGPA
CON	Month , Cognitive Strategy	MEA
CON	Month, $Month^2$, Cognitive Strategy	MEA
CON	Month, $Month^2$, $Month^3$, Cognitive Strategy	MEA
CON	$Month^2$, Cognitive Strategy	MEA
CON	$Month^3$, Cognitive Strategy	MEA
CON	Month , Cognitive Strategy	MEA, Gender, GPA
CON	Month, $Month^2$, Cognitive Strategy	MEA, Gender, GPA
CON	Month, $Month^2$, $Month^3$, Cognitive Strategy	MEA, Gender, GPA
CON	$Month^2$, Cognitive Strategy	MEA, Gender, GPA
CON	$Month^3$, Cognitive Strategy	MEA, Gender, GPA
CON	Month , Cognitive Strategy	
CON	Month, $Month^2$, Cognitive Strategy	
CON	Month, $Month^2$, $Month^3$, Cognitive Strategy	
CON	$Month^2$, Cognitive Strategy	
CON	$Month^3$, Cognitive Strategy	
CON	Month , Cognitive Strategy	Gender
CON	Month, $Month^2$, Cognitive Strategy	Gender
CON	Month, $Month^2$, $Month^3$, Cognitive Strategy	Gender
CON	$Month^2$, Cognitive Strategy	Gender
CON	$Month^3$, Cognitive Strategy	Gender
CON	Month , Cognitive Strategy	CGPA
CON	Month, $Month^2$, Cognitive Strategy	CGPA
CON	Month, $Month^2$, $Month^3$, Cognitive Strategy	CGPA
CON	$Month^2$, Cognitive Strategy	CGPA
CON	$Month^3$, Cognitive Strategy	CGPA
CON	Month , Cognitive Strategy	MEA

Independent Variable	Dependent Variables	Control Variables
CON	Month, $Month^2$, Cognitive Strategy	MEA
CON	Month, $Month^2$, $Month^3$, Cognitive Strategy	MEA
CON	$Month^2$, Cognitive Strategy	MEA
CON	$Month^3$, Cognitive Strategy	MEA
CON	Month , Cognitive Strategy	MEA, Gender, GPA
CON	Month, $Month^2$, Cognitive Strategy	MEA, Gender, GPA
CON	Month, $Month^2$, $Month^3$, Cognitive Strategy	MEA, Gender, GPA
CON	$Month^2$, Cognitive Strategy	MEA, Gender, GPA
CON	$Month^3$, Cognitive Strategy	MEA, Gender, GPA
EPS	Month , Cognitive Strategy	
EPS	Month, $Month^2$, Cognitive Strategy	
EPS	Month, $Month^2$, $Month^3$, Cognitive Strategy	
EPS	$Month^2$, Cognitive Strategy	
EPS	$Month^3$, Cognitive Strategy	
EPS	Month , Cognitive Strategy	Gender
EPS	Month, $Month^2$, Cognitive Strategy	Gender
EPS	Month, $Month^2$, $Month^3$, Cognitive Strategy	Gender
EPS	$Month^2$, Cognitive Strategy	Gender
EPS	$Month^3$, Cognitive Strategy	Gender
EPS	Month , Cognitive Strategy	CGPA
EPS	Month, $Month^2$, Cognitive Strategy	CGPA
EPS	Month, $Month^2$, $Month^3$, Cognitive Strategy	CGPA
EPS	$Month^2$, Cognitive Strategy	CGPA
EPS	$Month^3$, Cognitive Strategy	CGPA
EPS	Month , Cognitive Strategy	MEA
EPS	Month, $Month^2$, Cognitive Strategy	MEA
EPS	Month, $Month^2$, $Month^3$, Cognitive Strategy	MEA
EPS	$Month^2$, Cognitive Strategy	MEA
EPS	$Month^3$, Cognitive Strategy	MEA
EPS	Month , Cognitive Strategy	MEA, Gender, GPA
EPS	Month, $Month^2$, Cognitive Strategy	MEA, Gender, GPA

Independent Variable	**Dependent Variables**	**Control Variables**
EPS	Month, Month^2, Month^3, Cognitive Strategy	MEA, Gender, GPA
EPS	Month^2, Cognitive Strategy	MEA, Gender, GPA
EPS	Month^3, Cognitive Strategy	MEA, Gender, GPA
CAL	Month , Cognitive Strategy	
CAL	Month, Month^{2,} Cognitive Strategy	
CAL	Month, Month^2, Month^3, Cognitive Strategy	
CAL	Month^2, Cognitive Strategy	
CAL	Month^3, Cognitive Strategy	
CAL	Month , Cognitive Strategy	Gender
CAL	Month, Month^{2,} Cognitive Strategy	Gender
CAL	Month, Month^2, Month^3, Cognitive Strategy	Gender
CAL	Month^2, Cognitive Strategy	Gender
CAL	Month^3, Cognitive Strategy	Gender
CAL	Month , Cognitive Strategy	CGPA
CAL	Month, Month^{2,} Cognitive Strategy	CGPA
CAL	Month, Month^2, Month^3, Cognitive Strategy	CGPA
CAL	Month^2, Cognitive Strategy	CGPA
CAL	Month^3, Cognitive Strategy	CGPA
CAL	Month , Cognitive Strategy	MEA
CAL	Month, Month^{2,} Cognitive Strategy	MEA
CAL	Month, Month^2, Month^3, Cognitive Strategy	MEA
CAL	Month^2, Cognitive Strategy	MEA
CAL	Month^3, Cognitive Strategy	MEA
CAL	Month , Cognitive Strategy	MEA, Gender, GPA
CAL	Month, Month^{2,} Cognitive Strategy	MEA, Gender, GPA
CAL	Month, Month^2, Month^3, Cognitive Strategy	MEA, Gender, GPA
CAL	Month^2, Cognitive Strategy	MEA, Gender, GPA
CAL	Month^3, Cognitive Strategy	MEA, Gender, GPA
CUS	Month , Cognitive Strategy	
CUS	Month, Month^{2,} Cognitive Strategy	
CUS	Month, Month^2, Month^3, Cognitive Strategy	

Independent Variable	**Dependent Variables**	**Control Variables**
CUS	$Month^2$, Cognitive Strategy	
CUS	$Month^3$, Cognitive Strategy	
CUS	Month , Cognitive Strategy	Gender
CUS	Month, $Month^2$, Cognitive Strategy	Gender
CUS	Month, $Month^2$, $Month^3$, Cognitive Strategy	Gender
CUS	$Month^2$, Cognitive Strategy	Gender
CUS	$Month^3$, Cognitive Strategy	Gender
CUS	Month , Cognitive Strategy	CGPA
CUS	Month, $Month^2$, Cognitive Strategy	CGPA
CUS	Month, $Month^2$, $Month^3$, Cognitive Strategy	CGPA
CUS	$Month^2$, Cognitive Strategy	CGPA
CUS	$Month^3$, Cognitive Strategy	CGPA
CUS	Month , Cognitive Strategy	MEA
CUS	Month, $Month^2$, Cognitive Strategy	MEA
CUS	Month, $Month^2$, $Month^3$, Cognitive Strategy	MEA
CUS	$Month^2$, Cognitive Strategy	MEA
CUS	$Month^3$, Cognitive Strategy	MEA
CUS	Month , Cognitive Strategy	MEA, Gender, GPA
CUS	Month, $Month^2$, Cognitive Strategy	MEA, Gender, GPA
CUS	Month, $Month^2$, $Month^3$, Cognitive Strategy	MEA, Gender, GPA
CUS	$Month^2$, Cognitive Strategy	MEA, Gender, GPA
CUS	$Month^3$, Cognitive Strategy	MEA, Gender, GPA
RE	Month , Cognitive Strategy	
RE	Month, $Month^2$, Cognitive Strategy	
RE	Month, $Month^2$, $Month^3$, Cognitive Strategy	
RE	$Month^2$, Cognitive Strategy	
RE	$Month^3$, Cognitive Strategy	
RE	Month , Cognitive Strategy	Gender
RE	Month, $Month^2$, Cognitive Strategy	Gender
RE	Month, $Month^2$, $Month^3$, Cognitive Strategy	Gender
RE	$Month^2$, Cognitive Strategy	Gender

Independent Variable	Dependent Variables	Control Variables
RE	Month^3, Cognitive Strategy	Gender
RE	Month , Cognitive Strategy	CGPA
RE	Month, Month^2, Cognitive Strategy	CGPA
RE	Month, Month^2, Month^3, Cognitive Strategy	CGPA
RE	Month^2, Cognitive Strategy	CGPA
RE	Month^3, Cognitive Strategy	CGPA
RE	Month , Cognitive Strategy	MEA
RE	Month, Month^2, Cognitive Strategy	MEA
RE	Month, Month^2, Month^3, Cognitive Strategy	MEA
RE	Month^2, Cognitive Strategy	MEA
RE	Month^3, Cognitive Strategy	MEA
RE	Month , Cognitive Strategy	MEA, Gender, GPA
RE	Month, Month^2, Cognitive Strategy	MEA, Gender, GPA
RE	Month, Month^2, Month^3, Cognitive Strategy	MEA, Gender, GPA
RE	Month^2, Cognitive Strategy	MEA, Gender, GPA
RE	Month^3, Cognitive Strategy	MEA, Gender, GPA
VV	Month , Cognitive Strategy	
VV	Month, Month^2, Cognitive Strategy	
VV	Month, Month^2, Month^3, Cognitive Strategy	
VV	Month^2, Cognitive Strategy	
VV	Month^3, Cognitive Strategy	
VV	Month , Cognitive Strategy	Gender
VV	Month, Month^2, Cognitive Strategy	Gender
VV	Month, Month^2, Month^3, Cognitive Strategy	Gender
VV	Month^2, Cognitive Strategy	Gender
VV	Month^3, Cognitive Strategy	Gender
VV	Month , Cognitive Strategy	CGPA
VV	Month, Month^2, Cognitive Strategy	CGPA
VV	Month, Month^2, Month^3, Cognitive Strategy	CGPA
VV	Month^2, Cognitive Strategy	CGPA
VV	Month^3, Cognitive Strategy	CGPA

Independent Variable	**Dependent Variables**	**Control Variables**
VV	Month , Cognitive Strategy	MEA
VV	Month, Month^2, Cognitive Strategy	MEA
VV	Month, Month^2, Month^3, Cognitive Strategy	MEA
VV	Month^2, Cognitive Strategy	MEA
VV	Month^3, Cognitive Strategy	MEA
VV	Month , Cognitive Strategy	MEA, Gender, GPA
VV	Month, Month^2, Cognitive Strategy	MEA, Gender, GPA
VV	Month, Month^2, Month^3, Cognitive Strategy	MEA, Gender, GPA
VV	Month^2, Cognitive Strategy	MEA, Gender, GPA
VV	Month^3, Cognitive Strategy	MEA, Gender, GPA
RED	Month^2, Cognitive Strategy	
RED	Month^3, Planning	
RED	Month , Planning	Gender
RED	Month, Month^2 , Planning	Gender
RED	Month, Month^2, Month^3, Planning	Gender
RED	Month^2, Planning	Gender
RED	Month^3 Planning	Gender
RED	Month , Planning	CGPA
RED	Month, Month^2 , Planning	CGPA
RED	Month, Month^2, Month^3, Planning	CGPA
RED	Month^2, Planning	CGPA
RED	Month^3 Planning	CGPA
RED	Month , Planning	MEA
RED	Month, Month^2 , Planning	MEA
RED	Month, Month^2, Month^3, Planning	MEA
RED	Month^2, Planning	MEA
RED	Month^3 Planning	MEA
RED	Month , Planning	MEA, Gender, GPA
RED	Month, Month^2 , Planning	MEA, Gender, GPA
RED	Month, Month^2, Month^3, Planning	MEA, Gender, GPA
RED	Month^2, Planning	MEA, Gender, GPA

Independent Variable	**Dependent Variables**	**Control Variables**
RED	$Month^3$ Planning	MEA, Gender, GPA
CON	Month , Planning	
CON	Month, $Month^2$, Planning	
CON	Month, $Month^2$, $Month^3$, Planning	
CON	$Month^2$, Planning	
CON	$Month^3$ Planning	
CON	Month , Planning	Gender
CON	Month, $Month^2$, Planning	Gender
CON	Month, $Month^2$, $Month^3$, Planning	Gender
CON	$Month^2$, Planning	Gender
CON	$Month^3$ Planning	Gender
CON	Month , Planning	CGPA
CON	Month, $Month^2$, Planning	CGPA
CON	Month, $Month^2$, $Month^3$, Planning	CGPA
CON	$Month^2$, Planning	CGPA
CON	$Month^3$ Planning	CGPA
CON	Month , Planning	MEA
CON	Month, $Month^2$, Planning	MEA
CON	Month, $Month^2$, $Month^3$, Planning	MEA
CON	$Month^2$, Planning	MEA
CON	$Month^3$ Planning	MEA
CON	Month , Planning	MEA, Gender, GPA
CON	Month, $Month^2$, Planning	MEA, Gender, GPA
CON	Month, $Month^2$, $Month^3$, Planning	MEA, Gender, GPA
CON	$Month^2$, Planning	MEA, Gender, GPA
CON	$Month^3$ Planning	MEA, Gender, GPA
CON	Month , Planning	
CON	Month, $Month^2$, Planning	
CON	Month, $Month^2$, $Month^3$, Planning	
CON	$Month^2$, Planning	
CON	$Month^3$ Planning	

Independent Variable	Dependent Variables	Control Variables
CON	Month , Planning	Gender
CON	Month, $Month^2$, Planning	Gender
CON	Month, $Month^2$, $Month^3$, Planning	Gender
CON	$Month^2$, Planning	Gender
CON	$Month^3$ Planning	Gender
CON	Month , Planning	CGPA
CON	Month, $Month^2$, Planning	CGPA
CON	Month, $Month^2$, $Month^3$, Planning	CGPA
CON	$Month^2$, Planning	CGPA
CON	$Month^3$ Planning	CGPA
CON	Month , Planning	MEA
CON	Month, $Month^2$, Planning	MEA
CON	Month, $Month^2$, $Month^3$, Planning	MEA
CON	$Month^2$, Planning	MEA
CON	$Month^3$ Planning	MEA
CON	Month , Planning	MEA, Gender, GPA
CON	Month, $Month^2$, Planning	MEA, Gender, GPA
CON	Month, $Month^2$, $Month^3$, Planning	MEA, Gender, GPA
CON	$Month^2$, Planning	MEA, Gender, GPA
CON	$Month^3$ Planning	MEA, Gender, GPA
EPS	Month , Planning	
EPS	Month, $Month^2$, Planning	
EPS	Month, $Month^2$, $Month^3$, Planning	
EPS	$Month^2$, Planning	
EPS	$Month^3$ Planning	
EPS	Month , Planning	Gender
EPS	Month, $Month^2$, Planning	Gender
EPS	Month, $Month^2$, $Month^3$, Planning	Gender
EPS	$Month^2$, Planning	Gender
EPS	$Month^3$ Planning	Gender
EPS	Month , Planning	CGPA

Independent Variable	**Dependent Variables**	**Control Variables**
EPS	Month, $Month^2$, Planning	CGPA
EPS	Month, $Month^2$, $Month^3$, Planning	CGPA
EPS	$Month^2$, Planning	CGPA
EPS	$Month^3$ Planning	CGPA
EPS	Month , Planning	MEA
EPS	Month, $Month^2$, Planning	MEA
EPS	Month, $Month^2$, $Month^3$, Planning	MEA
EPS	$Month^2$, Planning	MEA
EPS	$Month^3$ Planning	MEA
EPS	Month , Planning	MEA, Gender, GPA
EPS	Month, $Month^2$, Planning	MEA, Gender, GPA
EPS	Month, $Month^2$, $Month^3$, Planning	MEA, Gender, GPA
EPS	$Month^2$, Planning	MEA, Gender, GPA
EPS	$Month^3$ Planning	MEA, Gender, GPA
CAL	Month , Planning	
CAL	Month, $Month^2$, Planning	
CAL	Month, $Month^2$, $Month^3$, Planning	
CAL	$Month^2$, Planning	
CAL	$Month^3$ Planning	
CAL	Month , Planning	Gender
CAL	Month, $Month^2$, Planning	Gender
CAL	Month, $Month^2$, $Month^3$, Planning	Gender
CAL	$Month^2$, Planning	Gender
CAL	$Month^3$ Planning	Gender
CAL	Month , Planning	CGPA
CAL	Month, $Month^2$, Planning	CGPA
CAL	Month, $Month^2$, $Month^3$, Planning	CGPA
CAL	$Month^2$, Planning	CGPA
CAL	$Month^3$ Planning	CGPA
CAL	Month , Planning	MEA
CAL	Month, $Month^2$, Planning	MEA

Independent Variable	Dependent Variables	Control Variables
CAL	Month, $Month^2$, $Month^3$, Planning	MEA
CAL	$Month^2$, Planning	MEA
CAL	$Month^3$ Planning	MEA
CAL	Month , Planning	MEA, Gender, GPA
CAL	Month, $Month^2$, Planning	MEA, Gender, GPA
CAL	Month, $Month^2$, $Month^3$, Planning	MEA, Gender, GPA
CAL	$Month^2$, Planning	MEA, Gender, GPA
CAL	$Month^3$ Planning	MEA, Gender, GPA
CUS	Month , Planning	
CUS	Month, $Month^2$, Planning	
CUS	Month, $Month^2$, $Month^3$, Planning	
CUS	$Month^2$, Planning	
CUS	$Month^3$ Planning	
CUS	Month , Planning	Gender
CUS	Month, $Month^2$, Planning	Gender
CUS	Month, $Month^2$, $Month^3$, Planning	Gender
CUS	$Month^2$, Planning	Gender
CUS	$Month^3$ Planning	Gender
CUS	Month , Planning	CGPA
CUS	Month, $Month^2$, Planning	CGPA
CUS	Month, $Month^2$, $Month^3$, Planning	CGPA
CUS	$Month^2$, Planning	CGPA
CUS	$Month^3$ Planning	CGPA
CUS	Month , Planning	MEA
CUS	Month, $Month^2$, Planning	MEA
CUS	Month, $Month^2$, $Month^3$, Planning	MEA
CUS	$Month^2$, Planning	MEA
CUS	$Month^3$ Planning	MEA
CUS	Month , Planning	MEA, Gender, GPA
CUS	Month, $Month^2$, Planning	MEA, Gender, GPA
CUS	Month, $Month^2$, $Month^3$, Planning	MEA, Gender, GPA

Independent Variable	**Dependent Variables**	**Control Variables**
CUS	$Month^2$, Planning	MEA, Gender, GPA
CUS	$Month^3$ Planning	MEA, Gender, GPA
RE	Month , Planning	
RE	Month, $Month^2$, Planning	
RE	Month, $Month^2$, $Month^3$, Planning	
RE	$Month^2$, Planning	
RE	$Month^3$ Planning	
RE	Month , Planning	Gender
RE	Month, $Month^2$, Planning	Gender
RE	Month, $Month^2$, $Month^3$, Planning	Gender
RE	$Month^2$, Planning	Gender
RE	$Month^3$ Planning	Gender
RE	Month , Planning	CGPA
RE	Month, $Month^2$, Planning	CGPA
RE	Month, $Month^2$, $Month^3$, Planning	CGPA
RE	$Month^2$, Planning	CGPA
RE	$Month^3$ Planning	CGPA
RE	Month , Planning	MEA
RE	Month, $Month^2$, Planning	MEA
RE	Month, $Month^2$, $Month^3$, Planning	MEA
RE	$Month^2$, Planning	MEA
RE	$Month^3$ Planning	MEA
RE	Month , Planning	MEA, Gender, GPA
RE	Month, $Month^2$, Planning	MEA, Gender, GPA
RE	Month, $Month^2$, $Month^3$, Planning	MEA, Gender, GPA
RE	$Month^2$, Planning	MEA, Gender, GPA
RE	$Month^3$ Planning	MEA, Gender, GPA
VV	Month , Planning	
VV	Month, $Month^2$, Planning	
VV	Month, $Month^2$, $Month^3$, Planning	
VV	$Month^2$, Planning	

Independent Variable	Dependent Variables	Control Variables
VV	$Month^3$ Planning	
VV	Month , Planning	Gender
VV	Month, $Month^2$, Planning	Gender
VV	Month, $Month^2$, $Month^3$, Planning	Gender
VV	$Month^2$, Planning	Gender
VV	$Month^3$ Planning	Gender
VV	Month , Planning	CGPA
VV	Month, $Month^2$, Planning	CGPA
VV	Month, $Month^2$, $Month^3$, Planning	CGPA
VV	$Month^2$, Planning	CGPA
VV	$Month^3$ Planning	CGPA
VV	Month , Planning	MEA
VV	Month, $Month^2$, Planning	MEA
VV	Month, $Month^2$, $Month^3$, Planning	MEA
VV	$Month^2$, Planning	MEA
VV	$Month^3$ Planning	MEA
VV	Month , Planning	MEA, Gender, GPA
VV	Month, $Month^2$, Planning	MEA, Gender, GPA
VV	Month, $Month^2$, $Month^3$, Planning	MEA, Gender, GPA
VV	$Month^2$, Planning	MEA, Gender, GPA
VV	$Month^3$ Planning	MEA, Gender, GPA

APPENDIX F

TIRE RELIABILITY MEA

NSF DUE-0717801 – CCLI-Phase 3 Comprehensive: Collaborative Research: Improving Engineering Students' Learning Strategies Through Models and Modeling.

SAFETY+TIRES, INC.

MEMORANDUM

TO: ENGINEERING 0020 CONSULTANTS

FROM: MORGAN PETERSON, VICE PRESIDENT OF ENGINEERING, SAFETY+ TIRES, INC.

SUBJECT: TIRE RELIABILITY

SAFETY+ has earned a national reputation for making high quality, long lasting tires. A tire failure on the road is not only a safety hazard that could result in a serious accident or even death, but it also reflects poorly on our reputation, which, directly impacts our bottom line and the bonuses that we can give out.

Consequently, making sure that our tires are as reliable as advertised is the number one priority of SAFETY+. Of particular concern is the attached article describing a recall of imported Chinese tires and the disastrous impact it will have on one of our competitors, Foreign Tire Sales. Unfortunately, we have recently received several customer complaints that raise concerns about the reliability of SAFETY+ tires. We need to know if these are isolated, independent failures, or if there is a reliability problem with one or more of our tire lines. Although it is highly unlikely that there is a problem, if your analysis suggests otherwise we might have to take action to resolve the problem. As you now must realize this could be extremely expensive, possibly requiring a recall of tires and a retooling of a plant. I trust that you clearly understand what the negative impact of a tire recall could be on our company. Consequently, we would like you to provide us with a robust procedure that our quality control technicians can use to determine if a particular production run has resulted in an acceptable level of reliability (as measured by time to failure). Because we plan to use this methodology throughout the company to continually monitor reliability, your procedure should be general, allowing quality control staff to use it for our various grades and production runs. (Note that we have six different grades with over 10 production runs each per year.)

Attached are the time to failure data (in thousands of miles) from three current production runs involving the tire grades of concern (SAFETY+ 25K, 50K and 100K) as well as our "gold standard." The gold standard data represents "acceptable reliability" for the 25K grade. As you are well aware, the 50K grade should have lifetime averages twice as long as the 25K and the 100K should have lifetime averages at least four times as long as the 25K grade.

As stated, we are requesting that you develop a general procedure that Quality Control can use to analyze the reliability of any set of tires based on such data. Once you have developed your procedure, you should use it to determine if each of the three production runs have resulted in acceptable reliability.

Please keep in mind that management is extremely concerned about what might be a potentially damaging situation, so your procedure and results should be solid and clear, as it could have a significant influence on the future of the company. Please mark your report CONFIDENTIAL.

Please do not share these results with anyone else either inside or outside of SAFETY+.

Part 1: Individual Assignment

1. Read the Memo from Morgan Peterson and the attached news article.

2. Answer the following questions:

a. Why is reliability important? Besides recalls, what other consequences could a company with reliability problems experience?

b. Give two specific examples of products, other than tires, where reliability is important.

c. A "reliability curve" shows the total number of products that have failed versus time. Describe what this curve might look like for a product such as tires.

Group Assignment: Tire Reliability

1. Before beginning, within your team compare each member's answers to the individual questions. If there are different responses, come to consensus on what the answers should be.

2. Reread the memo sent to your team from Morgan Peterson.

3. Morgan Peterson has provided tire data.

4. Write a memo to Morgan Peterson that includes:

- A reusable procedure to determine whether a set of data regarding tire performance is demonstrating acceptable reliability.

- The results of applying your reliability procedure to each of the three sets of tire data provided. For each set specifically answer:

  a) Do they have an acceptable reliability?

  b) Do the results show the tires have the correct treadwear grade?

5. Consider the last line of the Peterson Memo in which he specifically requests: “Please do not share these results with anyone else either inside or outside of SAFETY+.” Discuss this request with your team and prepare a separate, short essay that describes if there are any circumstances that would motivate you to ignore this request. If so, who would you discuss the results with? Do any of your results fall into this latter category.

Data for the Tire Reliability MEA

36.248	28.995	28.759	29.494	31.255	30.757	33.918
25.723	31.054	31.845	28.895	30.161	30.959	28.337
27.45	30.406	34.592	32.32	30.84	31.261	32.834
32.635	37.07	21.804	32.291	23.603	30.095	30.698
28.955	27.746	34.833	29.284	31.988	33.959	22.861
35.505	35.282	31.084	33.464	28.168	33.576	31.617
32.751	37.198	31.037	28.425	30.801	27.753	30.021
36.561	30.97	31.292	27.761	37.87	37.936	34.052
30.164	26.346	31.597	24.478	37.882	34.192	35.753
33.537	32.066	31.481	26.727	31.464	26.9	33.881
24.595	33.138	25.145	28.862	33.067	22.463	32.272
34.723	28.666	30.673	28.84	30.6	36.114	33.684
31.992	29.731	28.877	18.805	31.569	28.834	34.114
33.235	21.26	36.543	38.085	31.776	29.276	31.652
25.214	29.988	35.955	25.628	35.409	31.623	26.756
29.628	25.841	29.909	27.584	32.882	34.364	33.691
34.597	23.302	35.511	29.784	34.27	30.649	24.511
33.367	27.668	30.347	33.068	31.239	28.607	28.977
34.539	29.564	33.326	33.414	32.941	29.797	29.993
26.745	36.138	31.531	29.863	29.043	29.163	34.348
36.506	29.151	28.076	26.917	36.571	34.325	31.973
33.428	30.366	32.018	26.822	31.15	36.003	37.655
25.443	29.123	30.211	22.791	27.851	23.115	32.151
26.091	32.92	37.104	27.315	27.84	32.168	29.706
34.422	25.133	26.225	34.352	34.197	32.642	28.142
13.362	33.044	31.013	30.322	28.137	30.429	30.572
26.384	31.122	25.965	26.891	30.269	32.469	27.506
30.494	29.596	22.168	29.976	28.245	26.296	28.983
32.995	26.334	31.169	22.832	31.949	29.831	27.019
33.188	36.99	30.334	33.715	26.04	35.944	25.123
27.188	25.629	32.111	29.212	24.402	32.092	24.359
30.982	30.573	32.209	22.018	33.608	32.784	28.586
30.394	32.381	28.477	31.609	31.828	34.292	29.616
36.555	25.399	29.032	32.511	32.567	29.372	28.427
31.346	27.512	31.27	36.496	26.093	30.731	31.129
21.96	33.594	24.172	27.705	29.415	26.798	37.19
35.464	28.799	30.139	34.986	28.733	34.408	33.258
31.606	34.253	29.483	26.283	32.759	27.139	35.19
34.727	23.097	29.028	35.487	30.516	25.102	24.505
30.917	30.235	32.563	36.833	33.063	28.109	26.048
28.731	29.761	29.212	26.224	26.751	30.28	25.346
31.304	30.716	34.242	25.768	34.053	26.56	29.101
24.361	34.599	35.758	33.369	31.748	33.103	33.403
22.782	34.644	27.251	28.822	37.619	33.866	36.058
24.126	30.506	24.981	28.177	34.043	26.629	34.01
38.982	29.398	36.583	32.072	35.655	33.799	34.703
37.046	35.587	29.872	29.926	30.841	36.67	34.633
32.736	26.716	31.776	34.628	33.439	26.835	29.305
33.651	29.76	36.277	37.094	32.72	30.532	34.057
36.832	26.265	33.22	34.519	30.505	35.278	33.324
28.134	31.251	33.772	25.116	31.35	28.185	33.716
30.908	33.402	28.236	29.961	29.882	33.078	26.939

APPENDIX G

CNC MACHINE MEA

NSF DUE-0717801 – CCLI-Phase 3 Comprehensive: Collaborative Research: Improving Engineering Students' Learning Strategies Through Models and Modeling.

From: John Milgrom, Plant Manager

To: Christine Roberts, Engineering Analyst I

Re: Replacement of Barrand 250 CNC machine

Dear Ms. Roberts;

As mentioned in the production department meeting last week, we would like to purchase a Vanguard 360 CNC drilling machine to replace the Barrand 250 CNC machine for our products that require precision drilling. The Vanguard is likely to reduce the production time per unit from the current value. This new machine is also expected to reduce the production cost, while achieving the same or better precision. Since the capital cost for the new machines will not come out of our budget, any reduction in production cost and time, should enhance our end-of-the-year bonus.

In order to do this, we need to justify to Fred Johnson, Vice President of Operations, that we can increase the production level at a lower unit cost without sacrificing quality. Mr. Johnson, as you know, claimed at the last production meeting that we do not need this purchase now since we have extended the life of the Barrand CNC machine by another five years, due to the recent preventive maintenance program combined with the upgraded parts. I would like you to prepare a report that will convince Johnson and his staff that purchasing this CNC machine is not only critical to increasing production, but will also reduce the unit production cost. Further, your report should show that we are not likely to benefit from increasing economies of scale with our current machine.

Also, in your report, please address the management committee's concerns about the quality of the products produced by each machine. I am attaching the data that came from the tests that have been conducted on both machines. Keep in mind that the cost for the

Vanguard is $80,000. Vanguard has stated that the expected life of their machine is 15 years. We have estimated that we can sell our current machine for $15,000.

Please send your report to me first; include any concerns that you might have, as well as the detailed process that you followed when making your analysis. Also, include issues that you think could be a problem or that Johnson's people might raise at the next production meeting.

Although you have only been with us for six months, I know you are a qualified engineer who wants to be promoted to a better position and that you can produce a report that proves our point. I will be looking forward to hearing from you.

J. Milgrom

Plant Manager Engineer

Machine Name	Sample No	Unit Radius Drilled (mm)	Drilling Time (sec)	Drilling Cost ($)	Drilling Tool Used	Produ Withir Tolera
Barrand	1	12.5	4.2	0.65	1	YES
Barrand	2	11.4	3.8	0.71	1	NO
Barrand	3	13.4	2.6	0.64	1	YES
Barrand	4	14.6	3.3	0.70	1	NO
Barrand	5	14.5	3.9	0.50	2	NO
Barrand	6	14.8	3.2	0.34	2	NO
Barrand	7	11.1	3.6	0.33	3	NO
Barrand	8	12.6	3.1	0.45	3	YES
Barrand	9	14.5	2.7	0.30	3	NO
Barrand	10	11.6	4.0	0.34	3	NO
Barrand	11	12.0	3.5	0.86	3	YES
Barrand	12	11.2	3.4	0.51	4	NO
Barrand	13	11.1	3.4	0.35	4	NO
Barrand	14	11.7	5.0	0.39	4	YES
Barrand	15	11.9	4.7	0.29	5	YES
Barrand	16	11.1	3.7	0.38	5	NO
Barrand	17	12.1	3.4	0.35	5	YES
Barrand	18	12.4	4.0	0.53	5	YES
Barrand	19	13.2	3.2	0.34	5	YES
Barrand	20	12.4	3.7	0.40	6	YES
Barrand	21	12.5	3.5	0.62	6	YES
Barrand	22	12.4	3.6	0.32	6	YES
Barrand	23	14.6	3.0	0.28	6	NO
Barrand	24	12.9	3.7	0.32	6	YES
Barrand	25	12.7	5.3	0.91	6	YES
Vanguard	1	18.5	4.6	0.38	1	NO
Vanguard	2	15.6	4.9	0.37	1	NO
Vanguard	3	12.2	4.7	0.23	1	YES
Vanguard	4	11.9	4.2	0.55	1	YES
Vanguard	5	15.5	4.0	0.46	1	NO
Vanguard	6	12.5	4.2	0.47	1	YES
Vanguard	7	10.8	4.4	0.39	1	NO
Vanguard	8	17.1	4.5	0.41	1	NO
Vanguard	9	13.0	4.1	0.44	1	YES
Vanguard	10	12.3	4.2	0.45	1	YES
Vanguard	11	13.2	4.0	0.38	2	YES
Vanguard	12	12.9	4.8	0.36	2	YES
Vanguard	13	12.5	4.0	0.49	2	YES
Vanguard	14	11.7	4.2	0.44	2	YES
Vanguard	15	13.2	4.7	0.39	2	YES
Vanguard	16	12.9	4.4	0.24	2	YES
Vanguard	17	9.4	4.8	0.47	3	NO
Vanguard	18	13.1	4.5	0.58	3	YES
Vanguard	19	10.6	4.2	0.43	3	NO
Vanguard	20	16.1	4.7	0.57	3	NO
Vanguard	21	12.2	4.3	0.54	3	YES
Vanguard	22	14.9	4.6	0.33	3	NO

Memo 2-a:

From: John Milgrom, Plant Manager

To: Christine Roberts, Engineering Analyst I

Re: Establishment of the New CNC machine

Dear Ms. Roberts;

I have received your report. I regret to tell you that the report was not exactly in line with my expectations. I would like to give you another chance to work on the report, to make corrections since it is very important that we purchase the Vanguard machine.

Once again, we would like to prove the following points to the management committee in order to convince them that purchase is in the best interest of the company:

• Vanguard’s machine has shorter production time

• Vanguard’s drilling quality is better than Barrand’s quality

• Vanguard’s manufacturing cost per unit is lower than Barrand’s

I would like you to come up with a way to prove these points. Please think about the reasons why you were not able to come up with the same conclusion in your first analysis. Send me another report and describe your analysis in detail. Also, as you know, our new knowledge management system requires you to documents your process of thinking to come up with this solution. Make sure you add your process in the report too.

I hope that this time you will not disappoint the production department.

J. Milgrom

Plant Manager

Memo 2-b:

From: John Milgrom, Plant Manager

To: Christine Roberts, Engineering Analyst I

Re: Establishment of the New CNC machine

Dear Ms. Roberts;

I have received your report. I would like to thank you for the report and would like to know more about the details of it.

As you know, we would like to prove the following points to the management committee to convince them for the purchase of the new Vanguard CNC Machine:

- Vanguard's machine has shorter production time
- Vanguard's drilling quality is better than Barrand's quality
- Vanguard's manufacturing cost per unit is lower than Barrand's

I would like you to come up with additional ways to prove these points. Please think about the reasons why you were able to prove these points and what concerns the management committee might raise in regards to these results. Send me another report and describe your analysis in detail. Also, as you know, our new knowledge management system requires you to document your process of thinking to come up with this solution.

Make sure you add your process in the report too.

J. Milgrom

Plant Manager

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