AC 2010-627: SCALE DEVELOPMENT FOR ENGINEERING MODELING SELF-EFFICACY

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An Engineering Modeling Self-Efficacy (EMSE) Scale

Abstract

Self-efficacy is defined as personal judgments of one's capabilities to organize and execute courses of action to attain designated goals. Self-efficacy is shown to be a significant predictor of academic performance, academic motivation, students' participation in activities, rate of solution of arithmetic problems, and use of learning strategies. Students with high self-efficacy are likely to deal better with the challenges they face and develop strategies to solve them compared to students with low self-efficacy. In engineering education, there is a growing interest in self-efficacy due to its relationship to learning and future success.

Modeling is a fundamental aspect of engineering that is used to address complex problems. Particularly in engineering, modeling requires a process of abstraction where only the important details are represented via tools such as mathematical and computational languages. In the context of modeling, self-efficacy corresponds to one's perception of his or her modeling capabilities. When students are working on a modeling task, they normally encounter challenges resulting in iterations and updates to their solution methodology (process). A student with high levels of self-efficacy should, in theory, persist longer in modeling iterations and perform better in creation of conceptual and calculational models. In contrast, low self-efficacy may inhibit the student's effort even when the skill is present leading to discouragement.

A common approach to measure self-efficacy, particularly in the context of student work, has been to ask students to what extent they believe they can perform a certain task. However, as self-efficacy is task dependent and there is no common single method to measure it, we propose that a separate scale needs to be developed for modeling. This is particularly true for engineering students; as how self-efficacy beliefs impact their modeling abilities remains largely unknown.

In this study, we create an instrument to measure self-efficacy for modeling based on previous self-efficacy scales created for engineering design. The design scale was chosen for several reasons. First, it was developed for measuring self-efficacy of engineers specific to an important engineering capability. Second, it is a tested scale with high content and construct validity. In developing our modeling scale, we have used a similar approach: the subtasks of the modeling process are identified and listed and then students are asked how capable they believe they are in carrying each task. We have tested the scale using data from undergraduate engineering students. This paper serves as the first report of the results.

Introduction

Suppose two engineering students were given the same problem of creating a model of how the light switch works: one was able to do it, and the other could not. You observe that both students had the same level of schooling, achieved similar grades, and had similar experiences. Yet, what explains the unexpected difference in the outcome?

As educational psychology advances and engineering education research matures, we find that the differences in learning outcomes of students do not always stem from the controllable and observable attributes such as the courses taken, the assignments given, etc., but rather from students' hard to observe internal mechanisms. Such mechanisms regulate the extent to which students can comprehend the complexities of a real system and how much of this complexity they can reflect in a conceptual and calculational model.

Self-efficacy is one such mechanism that has been shown to regulate learning, motivation and academic performance of students. It is defined as personal judgments of one's capabilities to organize and execute courses of action to attain designated goals [1]. Individuals have high self-efficacy for a task when they believe they possess the capabilities necessary to successfully perform the task and low self-efficacy if they believe that they do not have the necessary capabilities. Hence, measuring self-efficacy of one's modeling ability is important in understanding the outcomes of the modeling task. Self-efficacy measurements are domain-specific; and, as noted above, there are no self-efficacy measurement instruments specific to engineering modeling currently available.

Here, we describe the development of a scale for the measurement of modeling self-efficacy. We provide a theoretical framework to show the predicted effects of self-efficacy on engineering modeling outcomes, and describe our process for the scale's development. Finally we provide pilot results of the self-efficacy scale and explain the implications and the limitations.

Background

a. Self-efficacy

Self-efficacy is a measure of performance capabilities rather than one's physical or psychological characteristics. It is important to focus on specific tasks and to assess efficacy perceptions and performance over a range of increasing task difficulty [2]. Self-efficacy arises from the gradual acquisition of complex cognitive, social, linguistic, and/or physical skills through experience [3].

One's self-efficacy beliefs are multidimensional and can vary based on the task that is assumed. Self-efficacy has three dimensions [4]: magnitude (level of task difficulty that a person believes he or she can attain); strength (whether the conviction regarding magnitude is strong or weak) and generality (the degree to which the expectation is generalized across situations). All three dimensions can influence the modeling abilities of students in different ways. Thus a self-efficacy instrument should be able to (1) break down the overall task into levels or subtasks; (2) obtain the degree of strength with which the subject believes she can accomplish the task and (3) have validity in various settings. Further, a student's modeling self-efficacy should be different from his self-efficacy in, say, problem solving. For our work, since we are primarily interested in classroom outcomes, the testing of the modeling self-efficacy instrument has been limited to engineering education environments.

The magnitude and strength of self-efficacy can influence one's choice of settings and activities, skill acquisition, effort expenditure, and the initiation and persistence of coping efforts in the face of obstacles [3]. In cases of higher self-efficacy, students have been shown to engage more frequently in task-related activities and to persist longer in coping efforts leading to more mastery experiences, whereas those with low self-efficacy give up more easily [2,3], ascertaining that self-efficacy can be a significant predictor of academic performance [5] , academic motivation [1], students' participation in activities [6] , rate of solution of arithmetic problems [7], and use of learning strategies [8]. Students with high self-efficacy are thus likely to better deal with the challenges they face and develop resolution strategies compared to students with low self-efficacy [9, 10]. These findings suggest that higher self-efficacy should be indicative of better modeling skills and outcomes in modeling.

In the context of modeling, self-efficacy beliefs correspond to one's perception of his or her modeling capability; i.e., the capability to create an abstraction of real world through use of natural (e.g. English) and / or symbolic languages (e.g. algebra, computer codes). Modeling in engineering requires development of a further set of skills that, to the novice user, at least, may be daunting. Obtaining higher modeling capabilities is a complex and somewhat troublesome process of integrating multidisciplinary engineering knowledge with creativity and implementation skills. These include establishing and maintaining a robust understanding of math and science, learning how to include the approximations of real life, searching for relevant information, creating a conceptual and subsequent mathematical model, using data within the model, testing the model results and further, and providing insight and validation on the obtained test results. It is expected that a particular level of self-efficacy is essential in overcoming the fear or anxiety that novice modelers experience in approaching an assigned task.

b. Modeling in Engineering

Broadly defined, 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 [11]. Modeling is the essence of thinking and working scientifically [12]. In cognitive science, models, and in particular mental models, refer to "representations of objects, processes or events that capture structural, behavioral, or functional relations significant to understanding these interactions [13].

Models are built to construct, describe or explain single or integrated systems. Narrowing the definitions for engineering, modeling here will 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 [14]. An engineering 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 [15].

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' [16], sometimes given the name *modeling cycle* [17]. The modeling process involves making decisions about relevant physical domains, abstractions, approximations, and other assumptions [16] .Thus modeling is a search of a space defined by multiple criteria. The modeling process is a constructive process since it involves putting together partial solutions under constraints and explicitly representing the information used to select, assemble, and evaluate the model. Depending on the purpose and focus of the research, modeling processes might look different [18]. For instance, Lesh and Harel [14] 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. Among the studies that address modeling process, Tsang's [19] is well suited to the modeling process in engineering. His steps of a modeling process are given in Table 1.

Table 1. Tsang's Description of Modeling Process

Step	Description
Review and Evaluation of Data	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.
Development of Conceptual Model and Potential Scenarios	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	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.
Construction of Calculational Models and Determination of the Associated Lumped Parameters	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, and Uncertainty Analysis	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	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. After the evaluation, if uncertainty in results is too large, the modeler should go back to the beginning and proceed again, if it is possible to obtain further data and update calculational models. If not, or the model

Step	Description
	provides good enough results, modeler can stop.
Validation	Ensuring that the model provides good enough reasons.

c. **Model Eliciting Activities**

Applications of modeling practices are increasing in engineering curricula. In particular, recently special modeling exercises entitled 'Model Eliciting Activities' (MEAs) have been introduced into the classroom [20]. MEAs offer significant benefits to engineering students in development of modeling and problem solving skills. In this work we take advantage of classroom implementation of MEAs to measure students' modeling self-efficacy.

As MEAs represent an increasing part of the engineering modeling literature, we provide some background below. An MEA is a thought-revealing, model-eliciting, open-ended, real-world, client-driven problem and a learning and assessment tool that is adapted to engineering [21]. MEAs were originally developed by mathematics education researchers to better understand and promote problem solving processes by encouraging students to build mathematical models in order to solve complex problems. MEAs were also created to provide a means for educators to better understand students' thinking. MEAs are built on the six principles given in Table 2.

Table 2. MEA Construction Principles[20,22].

Principle Description
Model Construction: Student team must create a mathematical model (system) that addresses the needs of a given client. A mathematical model: a system used to describe another system, make sense of a system, explain a system, or to make predictions about a system
Reality: The activity is set in a realistic, authentic engineering context and requires the development of a mathematical model for solution. A well-designed MEA requires students to make sense of the problem context by extending their existing knowledge and experience. The MEA should create the need for problem resolution, ideally making the student team behave like engineers working for the particular organization.
Self Assessment: As the model develops, students must perform self-evaluation of their work. The criterion for 'goodness of response' is partially embedded in the activity by providing a specific client with a clearly stated need. The criterion should also encourage students to test and revise their models by pushing beyond initial ways of thinking to create a more robust model that better meets the client's needs.
Model Documentation: The model must be documented; typically students write a memo to the client describing their model. The MEA is not only model-eliciting, but thought-revealing; i.e., the team's mathematical approach to the problem is revealed in the client deliverable. This process enables students to examine their progress, assess the evolution of the mathematical model, and reflect about the model. It provides a window into students' thinking, which can inform instruction.
Generalizability: The created model must be sharable, transferable, easily modifiable, and/or reusable in similar situations. It must be generally useful to the client and not just apply to the particular situation; i.e., it must be capable of being used by other students in similar situations, and robust enough to be used repeatedly as a tool for some purpose.

Effective prototype: The solution to an MEA provides a useful prototype, or metaphor, for interpreting other situations. The activity needs to encourage the students to create simple models for complex situations. The underlying concepts must be important ideas. Students should be able to think back on a given MEA when they encounter other, structurally similar situations.

We are using these six principles to improve an engineering student's understanding of engineering concepts, problem solving skills, as well as ethical reasoning and the ability of working in teams. The emphasis on building, expressing, testing and revising conceptual models is the most important difference between MEAs and 'textbook' problem-solving activities. Other differing characteristics of MEAs include the length of time required for solution, access to different information resources, number of individuals involved in the problem-solving process, and type of documentation required to solve an MEA. Since a typical MEA is implemented by a team of students as opposed to individuals (although some MEAs may be suitable for implementation by a single student), it therefore provides students with an opportunity to improve teamwork skills, which also reflects on their episode of learning. Finally, certain engineering MEAs may have an ethical dilemma embedded within the problem context, providing students with an opportunity to recognize and resolve ethical dilemmas.

MEAs have been used and tested in previous studies. For example, Diefes-Dux et al. [22] describe how to construct an MEA. Diefes-Dux and her colleagues introduced Purdue's first-year engineering to MEAs, and demonstrated that not only could they be effectively used to introduce concepts in engineering contexts. Ahn and Leavitt [23] summarize their experiences with MEA implementations and give recommendations to other educators. Diefex-Dux et al. [24] suggest using MEAs to advance the interest and persistence of female students in engineering. The authors point out that MEAs provide a learning environment that is tailored to a more diverse population than typical engineering course experiences as they allow students with different backgrounds and values to emerge as talented. Chamberlin and Moon [25] used MEAs as a tool to develop creativity and identify creatively gifted students in mathematics. They assert that the use of MEAs "provide students with opportunities to develop creative and applied mathematical thinking; and [enable instructors to] analyze students' mathematical thinking when engaged in creative mathematical tasks, aiding in the identification of those students who are especially talented in domain-specific, mathematical creativity" which is another potential benefits of MEAs.

Creation of a Modeling Self-efficacy Scale

Several overall self-efficacy scales have been created, under the name of general self-efficacy (GSE). GSE scales intend to measure belief in one's overall competence or "individuals' perception of their ability to perform across a variety of different situations" [26]. Yet, such overall instruments have proved to be insufficient for measurement of beliefs belonging to different tasks. Bandura [27], in his resource for researchers interested in creating a self-efficacy scale, states that "there is no all-purpose measure of perceived self-efficacy […] because most of the items in an all-purpose test may have little or no relevance to the domain of functioning". Despite the wide use of GSE scales, in light of Bandura's guidelines, we have not considered a GSE for measuring of modeling self-efficacy. In building our self-efficacy scale, we followed two essentials: first, we investigated other relevant scales in fields that are close to engineering modeling and academic setting, and second, we observed the guidelines suggested by Bandura. Pajares [28] provides a comprehensive list of the relevant efficacy scales for academic settings. We used his list of scales and added other available scales to create a comparison list of scales. This list is provided in Table 3.

Table 3. Major Self-efficacy Scales for Various Academic Tasks

Source	Sample Question or Direction	Answer Options
Teaching Efficacy [29]	How much can you …? [Completed by various teaching related tasks Influence the decisions that are made in your school]	1-9 Likert scale with 1=lowest
Mathematics problem solving self-efficacy [30]	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 Likert scale with 1=lowest
Self-Efficacy for self-regulated learning [31]	How well can you …? [completed by 11 self regulatory tasks]	1-7 Likert scale with 1=lowest
Self-efficacy for writing skills [32]	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- student writes the exact number
Mathematics courses self-efficacy [33]	How much confidence do you have that you could complete the following course with a final grade of B or better?	0 to 9 Likert scale
Collective efficacy [29]	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 Likert scale
Self-efficacy for performance division problems [34]	[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 [35]	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 Likert scale
Self-efficacy for academic achievement[31]	How well can you ... ? [completed by 9 academic domains-e.g. general mathematics, learn reading and writing language skills"	1 to 7 Likert scale
Self-efficacy for learning [36]	[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

An investigation of these self-efficacy scales reveals a few issues and generalizations available in the literature. First, as noted in the Table, all these scales are domain specific and serve distinct purposes; each is created to measure self-efficacy of a certain academic task. We conclude that a *separate self-efficacy for modeling scale should be built*. Second, almost all academic self-efficacy scales include a measurement of a task by providing immediate examples or a measurement content (i.e., they provide material for measuring the task). In the case of reading self-efficacy, students are asked to read a text; in the case of writing self-efficacy, they are asked to write one. Thus, we conclude that *when measuring self-efficacy of modeling, a relevant modeling task should be provided to the students* beforehand. Third, there is no agreement on a universal measurement option (i.e., some researchers use a 0-100 interval scale; others prefer a Likert scale, etc.). Bandura [27] suggests in his guide that a 0-100 interval is indeed beneficial; however, current scales available in the literature do not seem to necessarily follow this suggestion. We determined that a modeling self-efficacy scale can be developed using 1-5 Likert scale.

A particularly relevant self-efficacy scale to engineering modeling is an engineering design scale based on the scale of Carberry et al. [37]. This scale has provided an immediate relevant example for us in our creation of an engineering modeling self-efficacy scale and was chosen for several reasons. First, it is created for measuring self-efficacy of engineers, in the relevant concept of engineering design. Design of a system includes modeling abilities as well as problem solving skills. Second, this is a newer scale, ensuring that certain problems with older self-efficacy scales would not be repeated. Finally, it is a tested scale with high content and construct validity. Similar to the design scale, the subtasks of modeling process are identified and listed and students are asked how capable they believe they are in carrying out each task. In identifying the subtasks of engineering modeling, we utilized Tsang's adjusted modeling process definition. The scale that is created for engineering modeling, with the directions given to students while implementing the scale, is given in Appendix A. There are 36 items in the scale and it takes approximately 15 minutes to administer.

In the engineering modeling self efficacy scale, we asked students how well they think they could carry out the subtasks involved in modeling. We used a 1-5 Likert scale where "1" equals the lowest level of belief in one's skills for a particular modeling subtask and "5" the highest.

Testing of Modeling Self-efficacy Scale

a. Data collection

In this study, the data to test the Engineering Modeling Self-Efficacy (EMSE) scale was collected from a cohort of graduating senior and beginning sophomore engineering students. All students were chosen from undergraduates of Industrial Engineering field and they were varied in gender and academic skills as measured by their GPAs.

As mentioned, to test the scale, students engaged in a modeling exercise in concert with taking the self-efficacy instrument. Students were asked to solve two MEAs (i.e., Tire Reliability and CNC Machine Purchase MEAs, see www.modelsandmodeling.net for a copy) in teams of three to four students.

In addition to the student sample, for test purposes, we collected data from another 54 working engineering individuals, through online surveys of professional engineering organizations like ASME and ASCE. Seven data points of this second sample were deleted as they were incomplete. Thus, an overall sample of 67 was obtained. An initial analysis showed that the data from students and the working individuals both had similar factor structures.

b. Item and Factor Analysis

We followed Crocker's and Algina's [38] recommendations for scale reduction. The distributions (i.e., mean, standard deviation, skewness, and kurtosis) were examined for each of the 36 items of EMSE, which is given in Table 4. In EMSE, there are seven subscales that refer to Tsang's modeling process stages (Review and Evaluation of Data, Development of the Conceptual Model and Potential Scenarios, Establishment of Performance Criteria, Construction of the Calculational Models and Determination of the Associated Lumped Parameters, Modeling Calculations, Sensitivity Analysis, and Uncertainty Analysis, and Validation). We have determined, based on the definition of each stage described by Tsang, activities that fall under each of the stage and created the 36 items on EMSE. The stages and to which stage each items belong to are noted in Appendix A.

Items one to six pose questions related to review and evaluation of data that is to be used in modeling. These include deciding what data is necessary to test and evaluate the model, searching a database to find data to use in the model or to find other exemplary models to use as a starting point, determining whether the data on hand or found from the literature search is representative of the entire system the student is building the model for, deciding whether or not data on hand is coming from a reliable source and the sample size is large enough, identifying whether the data is relevant/ irrelevant for the model (and then clean the dataset accordingly) and develop a methodology to fill in the missing data where needed.

Items seven to 13 pose questions related to establishing a conceptual model and the relationships between parameters of the model. Under establishment of a conceptual model, we imply creation of the representational relationships between the variables and processes within the system. The relevant tasks for creating a representation of the system are developing a schematic representation of the system, identifying the (e.g. physical, biological or chemical) processes that are involved within the system, specifying the inputs and outputs of the system, finding out the relationships between processes within the system (create the conceptual model), determining the external conditions that can influence the system, determining the necessary conditions for a system to exist or function normally, and establishing the extreme cases of how the system function.

Items 14 - 16 relate to student's comprehension of what is to be measured quantitatively using the model (referred to as the performance criteria), such as determining how to make the performance criteria better. Items 17 - 22 pose questions related to the tasks of developing calculational or computational models to estimate the performance criteria, such as writing a computer program, planning out hand calculations, identifying the constraints, boundary conditions, etc. Items 23 - 27 relate to carrying out the actual calculations, checking out reliability and error of the calculations, and sensitivity analysis, 28 - 32 relate to transfer of the numerically found results back to qualitative information, or interpretation of the results, and finally 33 - 36 relate to validation of the overall model that is established.

Table 4. Review of Self-efficacy Item Scores

TSANG'S STAGE	ITEM NO	ITEM (MODELING TASK)	Mean	Standard deviation	Minimum	Maximum	Kurtosis	Skewness
Review and Evaluation of Data	1	Decide what data is necessary to use in the model	3.85	0.95	1	5	0.90	-0.86
	2	Search databases to find necessary data	4.13	0.75	2	5	-0.43	-0.44
	3	Determine whether the collected/ found data (sample) is representative of the population	3.91	0.81	1	5	1.34	-0.70
	4	Decide whether the data is reliable and size is large enough	3.85	0.83	1	5	1.24	-0.81
	5	Identify which parts of the dataset is irrelevant to the model	3.92	0.80	1	5	1.55	-0.76
	6	Develop/use a method to estimate missing data	3.77	0.73	2	5	-0.67	0.14
Development of the Conceptual Model and Potential Scenarios	7	Create a schematic representation of the system in two or three dimensions (create a prototype)	3.61	0.87	1	5	0.26	-0.42
	8	List the sub-processes that within the system (e.g. physical, biological, and/or chemical, economical relationships, etc.)	3.58	1.00	1	5	-0.63	-0.09
	9	Identify the relationships between sub-processes(how changes in one effects another)	3.90	0.89	2	5	-0.47	-0.45
	10	Identify inputs and outputs of the system	3.82	0.78	2	5	-0.56	-0.07
	11	Determine the (initial and boundary) conditions for the system to start/ stop functioning	3.55	0.93	1	5	0.34	-0.27
	12	Determine the necessary conditions for a system to exist/ survive once working	3.70	0.77	2	5	-0.23	-0.21
	13	Predict how the system will function in extreme cases	3.53	0.92	1	5	0.37	-0.58
Establishment of Performance Criteria	14	Determine the performance criteria to decide if the model is good enough	3.71	0.98	1	5	0.24	-0.59
	15	Determine whether the performance criteria chosen is appropriate for the system	3.70	0.80	1	5	1.00	-0.51
	16	Find ways to modify the performance criteria to make it better	3.78	0.87	1	5	0.54	-0.55
Calculational Models and Determination of the Associated	17	Quantify the impact of subprocesses on the performance criteria.	3.66	0.98	1	5	0.84	-0.86
	18	Simplify the relationships that exist in the system (make assumptions to simplify the relationships)	3.84	0.93	1	5	0.17	-0.60
	19	Identify the variables and parameters in the model	3.43	0.91	1	5	0.29	-0.36

	20	Identify the constraints of the model	3.61	0.89	1	5	0.04	-0.22
	21	Write a computer program to calculate the outcomes of the model	3.27	1.08	1	5	-0.37	-0.41
	22	Choose a mathematical/ statistical model to calculate the performance criteria/ results of a developed model	3.60	1.03	1	5	0.09	-0.48
Modeling Calculations, Sensitivity Analysis, and Uncertainty Analysis	23	Calculate the outcomes of the model by hand	3.52	1.03	1	5	-0.41	-0.36
	24	Calculate the outcomes of the model using a computer code	3.36	1.04	1	5	-0.66	-0.19
	25	Creating tables and graphs of the results (manual or computerized)	3.81	0.97	1	5	1.24	-0.92
	26	Determine the uncertainty in the parameters and data	3.66	0.91	1	5	0.64	-0.48
	27	Conduct a sensitivity analysis of the results	3.49	0.96	1	5	0.48	-0.72
Results Evaluation	28	Understand / evaluate the results of the calculated numbers	3.60	0.87	1	5	1.11	-0.80
	29	Determine if the results indicate an error	3.58	0.94	1	5	0.31	-0.41
	30	Use the results to predict future behavior of the system	3.66	0.77	1	5	2.72	-0.96
	31	Determine if the uncertainty in results indicates a need for an update or redesign of the model	3.30	0.85	1	5	-0.13	-0.17
	32	Explain the results	3.46	0.79	1	5	0.61	-0.46
Validation	33	Determine qualitatively if the developed model looks ‘alright’	3.81	0.91	1	5	0.50	-0.73
	34	Determine numerically if the model results are valid	3.70	0.87	2	5	-0.42	-0.37
	35	Determine ways to measure if the created model generates results in line with the actual system	3.75	0.80	2	5	-0.57	-0.04
	36	Determine how the model developed compares to other models of the same system	3.59	0.84	1	5	1.53	-0.88

For retaining items, a common rule of thumb is to have standard deviations be approximately 1 or smaller; and kurtosis and skewness within the +2 to -2 range (some authors also allow -3 to 3 range) [39]. These are standard in item reduction. Table 4 provides an initial indication that our items are normally distributed. Table 4 demonstrates that there are no items with very low or very high standard deviations, high kurtosis or skewness. Thus, no one item can be eliminated based on this analysis. The Cronbach’s alpha for the 36 item scale is 0.95, which confirms a high level of consistency (the commonly accepted level is 0.7 or higher).

Principal component analysis with orthogonal (varimax) rotation was used to examine the factor structures of the items. Orthogonal rotation was chosen because the correlations between factors calculated from the component correlation matrix were relatively low (r < 0.30) allowing the researchers in this study to assume independence of the factors. The number of factors extracted was based on three criteria: (a) the eigenvalue, (b) the percentage of variance, and (c) a scree test [40]. The decision to retain an item was based on the following two criteria: (a) an item-structure coefficient greater than 0.40 and (b) a minimum gap of 0.10 between salient coefficients on multiple factors [41].

Accordingly, three factors were retained. This factor solution explained 20% of the total variance. Item 25 was removed from the analysis as it failed to load on any of the three factors (highest loading was 0.37). This indicates that there is an overall modeling self-efficacy factor (i.e., factor 1), and that the two other main factors in EMSE are "use of data" (i.e., factor 2) and "determination of data and system conditions" (i.e., factor 3). As the determination of the factors was conducted based on pilot data, further analysis of the factors will be conducted after more data collection. The factor loadings for the 36 items are given in Table 5.

Table 5. Factor loadings for the EMSE Scale (loadings greater than 0.4 are highlighted)

ITEM NO	ITEM	Factor 1	Factor 2	Factor 3
1	Decide what data is necessary to use in the model			**0.54**
12	Determine the necessary conditions for a system to exist/ survive once working			**0.55**
2	Search databases to find necessary data		**0.67**	
3	Determine whether the collected/ found data (sample) is representative of the population		**0.54**	
5	Identify which parts of the dataset is irrelevant to the model		**0.55**	
4	Decide whether the data is reliable and size is large enough	**0.50**		
6	Develop/use a method to estimate missing data	**0.53**		
7	Create a schematic representation of the system in two or three dimensions (create a prototype)	**0.66**		
8	List the sub-processes that within the system (e.g. physical, biological, and/or chemical, economical relationships, etc.)	**0.59**		
9	Identify the relationships between sub-processes(how changes in one effects another)	**0.49**		
10	Identify inputs and outputs of the system	**0.52**		
11	Determine the (initial and boundary) conditions for the system to start/ stop functioning	**0.74**		
13	Predict how the system will function in extreme cases	**0.67**		

14	Determine the performance criteria to decide if the model is good enough	**0.73**
15	Determine whether the performance criteria chosen is appropriate for the system	**0.75**
16	Find ways to modify the performance criteria to make it better	**0.68**
17	Quantify the impact of subprocesses on the performance criteria.	**0.72**
18	Simplify the relationships that exist in the system (make assumptions to simplify the relationships)	**0.47**
19	Identify the variables and parameters in the model	**0.68**
20	Identify the constraints of the model	**0.61**
21	Write a computer program to calculate the outcomes of the model	**0.61**
22	Choose a mathematical/ statistical model to calculate the performance criteria/ results of a developed model	**0.64**
23	Calculate the outcomes of the model by hand	**0.68**
24	Calculate the outcomes of the model using a computer code	**0.57**
25	Creating tables and graphs of the results (manual or computerized)	0.37
26	Determine the uncertainty in the parameters and data	**0.63**
27	Conduct a sensitivity analysis of the results	**0.62**
28	Understand / evaluate the results of the calculated numbers	**0.63**
29	Determine if the results indicate an error	**0.67**
30	Use the results to predict future behavior of the system	**0.62**
31	Determine if the uncertainty in results indicates a need for an update or redesign of the model	**0.69**
32	Explain the results	**0.76**
33	Determine qualitatively if the developed model looks ‘alright’	**0.70**
34	Determine numerically if the model results are valid	**0.71**
35	Determine ways to measure if the created model generates results in line with the actual system	**0.75**
36	Determine how the model developed compares to other models of the same system	**0.62**

Content validity of the instrument is carried out by asking two experts to review the scale (i.e. Carberry and Zimmerman [42]). Both reviewers independently provided a positive feedback along with suggestions for change which were taken into account.

Discussion

This paper reports on an in-progress study to develop a self-efficacy scale for engineering modeling. With the help of existing literature, we developed and pilot tested a scale to measure the beliefs towards engineering modeling. The pilot testing with the scale demonstrated that scale items could be reduced to three primary factors.

Many students express finding modeling puzzling and challenging. Self-efficacy has been suggested as an important construct in students' academic achievements and an investigation for the role of self-efficacy in modeling should also be conducted. The present study provides a first step in this direction: we create and test a scale for engineering modeling self-efficacy. We thus extend the findings of previous research in engineering education and self-efficacy. In contrast to the global measures of self-efficacy suggested, the current scale provides detailed information about a set of engineering modeling tasks.

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Appendix A. Scale for Engineering Modeling Self-Efficacy (EMSE)

TSANG'S MODELING STAGE	ITEM NO	MODELING TASK	VERY POORLY (1)	POORLY (2)	JUST OK (3)	WELL (4)	VERY WELL (5)
Review and Evaluation of Data	1	Decide what data is necessary to use in the model					
	2	Search databases to find necessary data					
	3	Determine whether the collected/ found data (sample) is representative of the population					
	4	Decide whether the data is reliable and size is large enough					
	5	Identify which parts of the dataset is irrelevant to the model					
	6	Develop/use a method to estimate missing data					
Development of the Conceptual Model and Potential Scenarios	7	Create a schematic representation of the system in two or three dimensions (create a prototype)					
	8	List the sub-processes that within the system (e.g. physical, biological, and/or chemical, economical relationships, etc.)					
	9	Identify the relationships between sub-processes(how changes in one effects 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 working					
	13	Predict how the system will function in extreme cases					

Establishment of Performance Criteria	14	Determine the performance criteria to decide if the model is good enough					
	15	Determine whether the performance criteria chosen is appropriate for the system					
	16	Find ways to modify the performance criteria to make it better					
Construction of the Calculational Models and Determination of the Associated Lumped Parameters	17	Quantify the impact of subprocesses on the performance criteria.					
	18	Simplify the relationships that exist in the system (make assumptions to simplify the relationships)					
	19	Identify the variables and parameters in the model					
	20	Identify the constraints of 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					
Modeling Calculations, Sensitivity Analysis, and Uncertainty Analysis	23	Calculate the outcomes of the model by hand					
	24	Calculate the outcomes of the model using a computer code					
	25	Creating tables and graphs of the results (manual or computerized)					
	26	Determine the uncertainty in the parameters and data					
	27	Conduct a sensitivity analysis of the results					
Results Evaluation	28	Understand / evaluate the results of the calculated numbers					
	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 the results					
Validation	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					