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Characterization of Iterative Model Development in a Complex, Authentic Engineering Task

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Iterative Model Development by Students Engaged in an Authentic Engineering Task

I. Abstract

Model development has been identified as a core component in engineering practice. However, authentic modeling practices are difficult to replicate in the school environment. This case study investigates model iteration as it is practiced by a team of students as they engage in a complex, authentic chemical engineering task. Previously we have presented a method to characterize the modeling actions of student teams, termed Model Maps, which provide a graphical representation of student teams' model development as they proceed through the task. In this paper, we explore a team's iterative model development utilizing Model Maps generated from student teams' work products (notebooks, memoranda, final reports and oral presentations), in team meeting discussions, and in coaching sessions.

In analyzing instances of modeling, cycles of model iteration (generation, evaluation, use, revision, confirmation, and rejection) were observed. Details of the modeling process are revealed though a detailed analysis of this team's development of the Arrhenius equation. Their development transitioned from a vague understanding of the base equation to a more fully understood model component situated within the context of a larger predictive model. Students tended to be motivated to model by "dissatisfaction episodes." These episodes contain instances when disagreement exists between the student conception and another entity.

II. Introduction

Modeling is a core component of engineering practice. Development of the abilities to design and apply models is a goal of engineering education. This case study investigates model iteration as it is practiced by a team of students as they engage in a complex, authentic chemical engineering task. The task requires production of a product (silicon wafers with a thin film of silicon nitride) in a chemical deposition reactor. The specifications of the product qualities and the input parameters for the reactor are given. Our detailed analysis of the model iteration (generation, evaluation, use, revision, confirmation, and rejection) applied in completion of the task illustrates the diversity of models considered by the team and the complexity of model iteration applied by the teams. In this paper we provide a detailed analysis of one example of model iteration applied by a team. We show how team members identify the Arrhenius equation as a potential tool for the completion of the design task, their repeated interpretation and analysis of variables in the Arrhenius equation with respect to reactor input parameters, and how the input parameters influence the characteristics of the product.

Our research questions are:

What are the characteristics of model iteration as it is practiced by teams of engineering students as they engage an authentic engineering design task?
What types of models do students develop?
Which of models persist through out engagement in the task?
What information do students apply in the development of the models?

What motivates changes students make in the models?

This research contributes to the long term goal of our project to understand how engaging engineering students in authentic, ill-structured engineering tasks facilitates the development of their engineering skills.[1-3]

To facilitate students' authentic practice of these skills we have developed a learning system based on virtual laboratories. In this learning system, student teams take on the role of process development engineers. They are tasked with finding suitable input parameters to be released to high volume manufacturing through experiments that are completed virtually. When students perform experiments, the lower cognitive demand affords them the opportunity to build a rich experimental design. While not instructed to do so, most student teams inevitably resort to modeling as a tool to progress towards completion.

Student team modeling practices are captured and analyzed via a previously reported method termed "model mapping." In the model map analysis process the models students propose as they work toward completion of the task are found in the student's work products (notebooks, memoranda, final reports and oral presentations), in team meeting discussions, and in coaching sessions. Those models are recorded in and organized chronologically in a graphical format. With the team's model map complete, models which undergo iteration will become readily identifiable for analysis in this work. In this study, one team (Team A) was recorded during their team meetings and coaching sessions in an effort to more fully capture their behaviors.

Through the model map of a particular team, the use of an iterative model approach
Through the analysis of Team A's model map and protocol transcripts, the team's utilization iterative modeling practices was observed. This iterative method involves the generation of models; the evaluation or use of those models; and the revision, confirmation, or rejection of models. Student methods tend to progress forward using a generation-evaluation-revision structure, but there are instances of deviations at any step in that process. This progression aligns with research that shows iterative modeling behavior in practicing professionals.[4]

III. Background

Modeling is a core skill for many disciplines and professions. The body of research related to the characterization of modeling behavior is better developed in some areas than it is in others. For instance, there is much more research on modeling in the scientific disciplines than modeling in engineering practice. The research in science and engineering demonstrates the diversity of model types and of the functions models serve. Consistent across the research is agreement on the importance of modeling in the practices of science inquiry and of engineering design. This background section focuses on the importance of modeling in engineering and how disciplinary models of science principles are involved in the modeling practice of students in this study. The theoretical framework for this study acknowledges the iterative nature of modeling in engineering practice and the application of models of science principles (e.g. the Arrhenius equation) and their modification to fit the requirements of the engineering task.

Modeling in Engineering Practice

English and Mousoulides[5] argue that the "heart" of engineering consists of both the engineering design process itself and "the creation, application, and adaptation of mathematical/scientific models that can be used to interpret, explain, and predict the behaviour of complex systems." The Accreditation Board for Engineering and Technology (ABET) has emphasized the importance of modeling through their thirteen Fundamental Objectives of Engineering Instructional Laboratories.[6] The importance of models in engineering education is also reflected in the content of engineering texts and books on modeling for practicing engineers. See for instance references.[7-11]

Philosophers of science have observed the centrality of models and model formulation to the progress of science[12] and similarities between scientists' and engineers' use of models in their practice.[13] Science educators have suggested that models and modeling can serve as a bridge between science education and engineering education.[14]

What is a Model?

When referring to models, researchers and philosophers focus on what a model is and the function it serves. In engineering, three features are the most prominent. First, models tend to simplify phenomena[15]. Simplified models lend themselves toward a wide variety of applications and can often provide an engineer with a cost effective solution to a problem. Second, models can have predictive power.[16,17,18] Predictive models lend themselves toward effective design because they yield some level of optimization before the user performs real experiments or buys expensive equipment. Lastly, models can explain interesting phenomena[19,20,21]. Creating a model and testing it against a target system forces the user to think about and eventually find explanations for the parts that do not agree.

For this body of work, we will include these key behaviors in a single model definition that describes a model as "a representation that abstracts and simplifies a system by focusing on key features to explain and predict scientific phenomena."[16] Even with this distinction, models can take on many different forms. Two important distinctions for this work are discussed below.

Quantitative Models

Quantitative modeling, also known as mathematical modeling, is broadly defined as the representation of a system through the use of mathematical equations.[5,22,23] Generally, relationships within the target system, such as the relationship between temperature and growth rate in the Virtual CVD Laboratory Project, are characterized through the development of quantitative models. When developed appropriately, the model gains predictive power in the form of a numerical prediction.

Qualitative Models

There are a wide variety of types of qualitative models, including: inscriptions, which involve the use of tables, diagrams, graphs and maps;[5] propositions, which are considered the smallest unit of knowledge that one can sensibly judge as true or false; and metaphors, which allow conceptual leaps across domains.[23]

Model Components

When faced with complex situations, researchers have the observed tendency to break the target system into smaller pieces based on interesting and observable features in an effort to make sense of the system in question.[17,24] In this work, those pieces are called *model components.* Model components make it easier for the user to engage the different aspects of a complicated system, and often come from different areas within the user's background.

Graphical Representations of STEM Learning

Graphical representations are emerging as a method for learning scientists to link the goals of an instructional intervention with observations of students' actions, and through this linkage to provide evidence of learning.[25-30] In general, such graphical representations allow characterization and interpretation of more complex and extensive activities. They also form a holistic and complementary alternative to the statistical analyses of quantitative methods or the fine grained but discrete analyses of qualitative methods such as discourse analysis. While each is unique, the graphical representations all contain the following common characteristics. They are:

- Visual, chronological, holistic and integrative (summarizes significant features of the entire learning experience)
- Used to interpret and illustrate interactions or relations between desired elements of study
- Uniquely constructed for each research study based on instructional design and research questions to examine the understanding and performance that the researchers desire to study
- Complex to interpret, and typically hard to make methodology transparent
- Different in the granularity of analysis (scales with extent of project)

IV. Theoretical Framework

The process of modeling has been described as a process of generation, evaluation and modification, or GEM cycle.[4,31] Model generation is hypothesized to be a response to observation and to the focus of one's attention, which can be guided by previous models.[4] In a complex system, this has a number of implications regarding the iterative development of multiple models. In particular, for a target model A and a peripheral model B, changes in model B can effect model A without the mathematical or descriptive form of model A being adjusted. This is due to the change in focus of the user's attention. When new features or relationships become apparent, different aspects of the applicability of model A may become apparent.

In the next stage of modeling, evaluation, any number of influences cause a user to consider changing the target model. Interactions with the target system (use of the model or other interaction) or other representations can prompt the evaluation process.[32,33]

Finally, the result of model evaluation can resolve in one of three ways: through reinforcement (also called confirmation), revision, or rejection.[31,34] When a model is reinforced, the event that caused the model's evaluation coincides with the model's behavior and it is more confidently used in its present form and context. A reinforced model can be put through the evaluation process again if something influences the user. If the model evaluation event does not coincide with the model's behavior, a user can revise the model (make adjustments to account for the mismatched behavior) or reject the model. When a model is rejected it can be considered again in the future, or dropped permanently in favor of the start of a new modeling cycle.

This body of work intends to investigate the structure of modeling in a student team's work through the case study methodology[35] using this framework as a guide. We will use our group's graphical representation method (model maps) to identify the instances of model reoccurrence and utilize information in the team's work products and meeting transcripts to characterize the cycle of model development utilized by students.

V. Methodology

Project Setting

The study presented in this paper focuses on the Virtual CVD Laboratory Project,[1,2,36] in which student teams are tasked with developing a 'recipe' of input parameter values for a chemical vapor deposition (CVD) reactor. The reactor deposits thin films of silicon nitride on polished silicon wafers, an initial step in the manufacture of transistors. The computer simulation generates data for film thicknesses at the wafer locations students choose to measure based on their specified input parameters. The film thicknesses incorporate random and systematic process and measurement error and are representative of an industrial reactor. The student teams must use results from successive runs to iteratively guide their solution. They are also encouraged to apply sound engineering methods as they have a limited budget and they are charged virtual money for each reactor run and each measurement. Student teams continue until they have found a 'recipe' of input parameter values that they believe yields optimal reactor performance. This project is complex and participants typically spend between 15 and 25 hours to complete the project. More information may be found in Reference 1.

Participants

Student participants were from the same cohort in the first term of the senior capstone laboratory sequence at Oregon State University. This class included 27 students majoring in bioengineering, 45 students majoring in chemical engineering, and 9 students majoring in environmental engineering. These students were assembled into 27 three-student teams who all participated in the virtual laboratory project which was administered between two physical laboratory projects. They had a choice between the three virtual laboratory projects; 15 teams worked on the Virtual CVD Laboratory Project (45 students) and the remainder worked on a different virtual laboratory project. This research was approved by the institutional review board and the results reported here are from participants that signed informed consent forms.

Data Collection

Data sources include audio recording of student teams and their work products. Teams were audio recorded whenever the team met to work on the project. Thus far, four teams have been audio recorded and transcribed. One team, Team A, is focused on in this paper. Student work products included the teams' laboratory notebook, their design memoranda, and their final report. Laboratory notebooks are intended to contain all ideas and notes over the course of the project and provide evidence of the models that student teams use as well as their model progression and the strategies that they consider. This source is complemented by the written assignments and the experimental records from the virtual laboratory database. All of these sources serve to confirm, explain or expand upon the content of the transcripts.

Data Analysis: Model Maps

Model Maps are used to provide a visual depiction of student modeling during the laboratory project. These maps categorize the model component type (quantitative, qualitative, statistical or empirical), their degree of utilization (operationalized, abandoned or not engaged), their correctness, and the experimental runs to which they are relevant. This information is chronologically arranged along with the experimental runs and instructor consultations to give an appropriate context to the team's work. In total, 42 Model Maps have been completed and analyzed based on student work products.[37] A brief description of the elements contained in a Model Map is provided below; more detail is available in reference 38.

Model components are identified in student teams' work products or in the transcripts of the teams' project meetings. A student researcher assembles this information and constructs the preliminary Model Map. A faculty member, who is a domain expert, then reviews and evaluates this information for accuracy and correctness. The separation of the student researcher's production of the preliminary Model Map the domain expert's review is done intentionally to ensure consistency and reliability. The two meet and discuss until consensus is reached. Features relevant to this study are highlighted below.

Model Components

Modeling components are identified when it is clear that the use of this component furthered, or intended to further, the team's progression toward a solution. Once the component is identified, a description or mathematical expression is added to the Model Map.

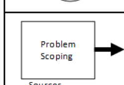
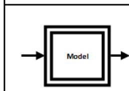
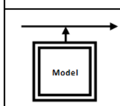
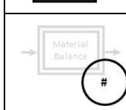
Table 1 displays the types of modeling components. Quantitative Model Components, characterized by the use of mathematical expressions or reasoning, are placed inside squares, while Qualitative Model Components, characterized by descriptive or intuitive mechanisms, are placed inside circles.

The line which surrounds the model component represents the type or level of engagement associated with the particular model component. A model component surrounded by a double line represents a model which has been operationalized and retained by the team. A model component surrounded by a single line represents a model component which has been considered, but ultimately rejected.

A team may reject a component when mathematical errors prevent its usefulness, when the data contradicts the hypothesis posed by the model, or when a more correct or relevant version of the same model component is discovered later. Model components surrounded by dashed lines are considered to be "not engaged". These model components appear where there is no evidence of utilization in mathematical work; there are no changes evident in their run parameters, or otherwise.

Model components that are placed on the center line are considered central to the team's approach to the project and are designated as "Primary Model Components". Models that lie outside the center line, connected by inward arrows are considered "Secondary Model Components", which can be seen in the second part of Table 1. Some model components are presented as groups which connect to each other vertically. These model components are considered to be "chunked" together by the student team. Chunking can be differentiated from the serial development of individual model components by a student teams' use of mathematics to bind the individual model components together or by the use of a through written or verbalized description of the model components they see as belonging together. This formation is indicative of high level modeling.

Table 1. Model Component and Run Key

	Symbol	Name and Description
Type of Model Component	○	Circles represent **qualitative model components**; relationships that do not rely on numbers, e.g. *"As pressure decreases, uniformity increases"*
	□	Rectangles represent **quantitative model components**; relationships that rely on numbers (typically in the form of equations), e.g. "*Film Deposition Rate=Reaction Rate Constant x Concentration of Reactant*"
Modeling Actions	◎	An **operationalized model component** is one that is developed and then used throughout the solution process.
	○	**Abandoned model components** are developed and then clearly abandoned.
	◌	A model component is classified as **Not Engaged** if it is clearly displayed in the notebook but no evidence exists of its use.
Run Type	■	A quantitative model is used by the group to determine the parameter values for **model directed runs**.
	▲	A statistical approach is used to determine the parameter values for **statistically defined runs** (e.g. DOE)
	●	Teams analyze the data provided by **qualitative verification runs** to qualitatively verify models that they have developed.
	▮	No explicit reason is given or deducible for **runs not explicitly related to modeling**. Often they represent a "guess and check" or a "fine tuning" run.
Additional Descriptors	⊗	An X is placed over any **clearly incorrect model component**.
		A box is shown at the beginning of the map, signifying the **Information Gathering** stage. All sources listed in notebook are displayed.
		**Primary model components** are along the central problem line and are used repeatedly and are essential to the overall solution.
		**Secondary model components** are connected to the central problem line and are peripheral to the overall solution
		A **run reference number** denotes the run(s) which a given model component was explicitly applied.

Experimental Run Markers

Critical to the model development process in the Virtual CVD Laboratory Project is the information teams obtain from the experimental runs they complete. Experimental runs are included in the Model Maps, indicated by run markers on the center line with a corresponding run number. As shown in the bottom of Table 1, the relation between the runs and the team's model development is also identified. Separate symbols are used for: (i) Model Directed Runs (filled squares), runs where the input values have been generated by the team's model; (ii) Parameter Defining Runs (filled diamonds), runs which are used to collect data necessary to obtain a numerical value for a model parameter (e.g., activation energy); (iii) Statistically Defined Runs (filled triangles), runs which are part of a statistical design (e.g., Design of Experiments), or (iv) Qualitative Verification Runs (filled circles), runs which confirm or contradict qualitative model predictions. Experimental runs which cannot be classified in any of these categories are said to have no relation to modeling and have their own appropriate run marker. Run numbers which appear near model components indicate the relevance of that run in the development or use of that model component.

Data Analysis: Iterative Stage Coding

The model map produced from the student team meeting transcripts was used to identify the model components that were reoccur throughout the team's solution pathway. The transcript locations that corresponded to the iterated model components were then extracted and coded with respect to the stages of generation, use/evaluation and modification/confirmation/rejection.

VI. Results and Discussion

A model map for one student team, henceforth referred to as "Team A", has been completed. Through this, the types of models utilized by this team can be characterized. In the development of their solution Team A considered 34 different model components, 5 of which were quantitative model components (e.g. the rate equation) and 29 of which were qualitative (e.g. "flow rate does not affect pressure").

As Team A's solution pathway was characterized, iterative model development strategies were observed. To provide a description of the team's iterative strategy; an explanation of a sample process regarding their struggle in taking utilizing the Arrhenius equation is presented. Over the course of five modeling instances, Team A works toward placing the model within the context of the virtual laboratory process and the desired outcomes of the task.

Arrhenius Equation: An Example of Student Model Component Iteration

The Arrhenius equation provides a relationship that relates temperature to reaction rate through the reaction rate constant. In the context of this project, it is useful for predicting the amount of deposition that will occur on the wafers in the virtual CVD reactor. This model component first occurs while the team is exploring the temperature and flow rate parameters. The team identifies the Arrhenius equation as potentially relevant (generation).

Student 1: We haven't done any research on flow rates though
Student 3: Yeah the only thing we have is the correlation of stoichiometry and the fact that we're going to want more NH3 than stoichiometry dictates.
Student 1: Our values were based on research. Models will
Student 2: Decrease in the gas flow rate originally affects the temperature
Student 3: So the temperature relates to this whole thing once for diffusion rate, twice for reaction rate
Student 1: Good point, I should write that down. It's like, I know it is e to the negative E over … I told him to look it up and he's looking it up I was just trying to remember it for fun but I think I am failing.
Student 2: Got it
Student 1: So Arrhenius equation says there's a lot of forms of it but it is saying that our reaction rate, k=, it's k over, something over C_0.
Student 2: It's C/C_0 =RT
Student 1: That type of thing yeah, T/T_0, okay I am getting nowhere. Okay so, I am finding it, okay go back to those equations, let's see what A is.
Student 2: A is the pre-exponential factor simply preferred…
Student 1: Okay just go back, this isn't that important right now

The team initially incorporates the Arrhenius equation by considering the effects of the input parameter temperature. They correctly identify temperature affects both diffusion and reaction rates, and recall the approximate form of the equation, but need an internet resource to write the quantitative form. They discuss the form of the equation, before dismissing it as not "that important right now (evaluation, rejection). The team's behavior and resource use around this Arrhenius modeling instance implies the likely use of Wikipedia in their search for the Arrhenius equation. Based on the sites used and the pieces of the equation discussed, it is reasonable to say that the students were attempting to engage the modified form of the Arrhenius equation presented on that site:

$$k = A\left(\frac{T}{T_0}\right)^n exp\left[-\left(\frac{E_A}{RT}\right)\right]$$

The next consideration occurs after the team completes their first experimental run and tries to make sense of their experimental data. Student 1 suggests the idea of a predictive model to the rest of the team. The idea is initially met with confusion, but after explaining the usefulness of previous data provide toward model generation, Student 3 goes on to describe a potential pathway for this work.

Student 1: Wouldn't it be interesting if we could come up with an equation that predicted the thickness based on concentration at that point and temperature, using the data
Student 3: Say what?
Student 1: Because you have like 10 points to look at. You could use the data to come up with an equation that relates the temperature to a specific point to concentration and thickness.
Student 3: It would work for all instances of the flow we have. If we change the flow it will mess up that entire relationship.
Student 1: But it would give us an idea. It's going to be a weird equation.
Student 3: If it is reaction rate limited then there's a constant that doesn't change. The rate equation is represented by an Arrhenius type equation which is $k_s = k_0$ e^(E_A/kT). The k and the kT will change as temperature changes but the k_0 doesn't change. So if we could figure that out for the case of this

dichlorosilane reaction for whatever changes we make which will be kind of nice.

…

…

Student 1: It's going to be kind of hard so what you have to do is you have to know that you start out at a certain amount of concentration based on what you are feeding and then how much gets taken away from the first wafer and then the next concentration point would be between the 2 and that will be that minus. And then you do it for all the points keep subtracting more and you know would how much you have at the end
Student 2: How do we calculate how much is consumed by each one?
Student 1: Based on the thickness we know the volume of the
Student 2: Because these react, so we would have another column for what they are forming
Student 1: I know, it's kind of hard. It's only going to be useful if we can see it every time we do this
Student 2: Yeah
Student 1: Not versus one time because it's going to be a lot of work.

Student 3 identifies a form of the Arrhenius equation which includes the Boltzmann constant in the effort to describe an appropriate modeling approach for the team (evaluation, revision). Student 1 chimes in later to describe the type of mass balance (a core concept chemical engineering concept used to validate one of the student's input parameters) necessary to allow the team to better incorporate the Arrhenius equation in the context of the engineering design task. In this form of the equation, the team is missing the negative sign before the activation energy (E_A).

$$k_s = k_0 exp\left[\left(\frac{E_A}{kT}\right)\right]$$

The team's conversation takes a turn when one of the students completes a calculation related to one of their project metrics. They soon move toward completing more experimental runs and this modeling conversation subsides. Between team meetings days, Student 3 creates a predictive model that consisted of many different model components. This included the Arrhenius Equation in its most recent form, a material balance, and a reaction rate expression (revision, due to its integration with other model components). These three expressions are shown in order below.

$$k_s = k_0 exp\left[\left(\frac{-E_A}{k_B T}\right)\right]$$

$$mass\ in - mass\ out = mass\ accumulated - mass\ consumed$$

$$G = \frac{C_T k_s Y}{N_1}$$

The Arrhenius equation underwent minor corrections when Student 3 engaged it. Namely, the Boltzmann constant is relabeled and a negative sign now appears before the activation energy. This predictive model is used to determine input parameters for the team's fourth experimental run. Upon seeing the results, Student 1 expresses "okay. I really like the temperatures that came out, a 100%" (use). When the predictive model was constructed, a literature value for the activation energy was used. During Team A's update meeting with their coach, their method for obtaining the activation energy comes under question.

> **Coach**: What activation energy did you use?
> **Student 3**: I used 1.49 electron volts
> **Coach**: ok and where did you get that?
> **Student 3**: The website is on a sticky downstairs. I'll put it in the appendix.
> **Coach**: And that is silicon nitride CVD?
> **Student 3**: Yep
> **Coach**: So you have runs at 2 temperatures here. Pressure is a little different and flow rate is a little different but from the growth here can you estimate activation energy?
> **Student 3**: We should be able to. We should be able to make a graph of growth rate versus temperature and estimate the activation energy from there.
> **Student 1**: We had a philosophical debate about that yesterday whether we should get it from online or whether we should calculate it from our results. And he won because he is the one working on it.
> **Student 3**: Well at first we were just going to take the rate equation based on the growth rate and then solve for 2 unknowns using 1 equation. But I saw online that you can make a graph of growth rate versus inverse temperature and you can get an activation energy off of that. The flow rates are going to have to be the same every time but I think we have a few runs that are of the same flow rate.

The team is asked about estimating activation energy and Student 3 remembers reading about the Arrhenius graph, a method that utilizes graphed data to determine the activation energy (evaluation). Realizing that specific data was required for this calculation, Team A uses their current predictive model to tailor two experimental runs to get the required data (use).

$$\ln(k_s) = \frac{-E_A}{R}\frac{1}{T} + \ln(k_0)$$

To obtain the activation energy, the above form of the Arrhenius equation is used. In that graph, the natural logarithm of k_s is plotted against T^{-1} which result in a line with the slope E_A/R. The new activation energy value is integrated into their predictive model and the model is used several times more (revision, use). Finally, near the end of the project, the team determines that the predictive model is no longer accurate enough to fine tune their model (evaluation, rejection). They change strategies and "tweak" the parameters to finish the project.

The Arrhenius equation was visited five times by this team: the first team meeting, after their first experimental run, as part of the first predictive model formulation, during their update meeting, and during their activation energy adjustment. During this time, thirteen iterative stages can be observed. Moreover, with each successive consideration, the team more effectively incorporated this component into a process model to predict film thickness.

Iterative Modeling throughout the Project

This example is just one observed iterative modeling efforts worked out by Team A. Figure 1 shows a more complete depiction of the modeling effort in the form of a model map. The five considerations of the Arrhenius equation are shown, including, in the problem scoping phase, after the first experimental run (solid rectangle labeled by a "1" above it, after run 3 where it is used to predict the run parameters for experimental run 4 (indicated by a square labeled by a "4:" above it, and right after the second instructor consultation. Also shown in Figure 1 are seven other iterated model components. Each separate component is by a repeating letter, which is defined in Table 2.

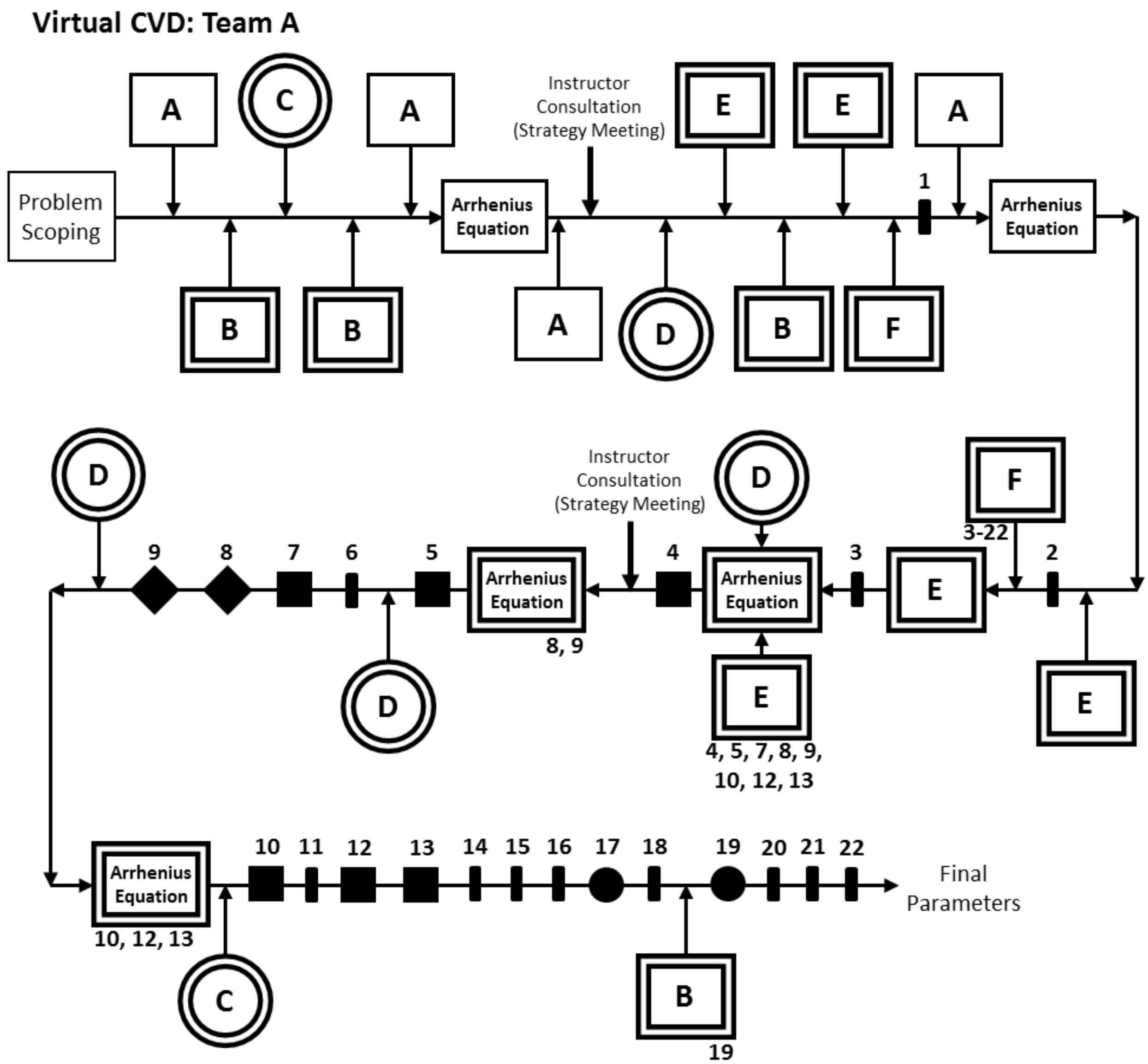


Figure 1. Transcript-Based Model Map for Team A. Unique model components are identified with unique letters. Model components that do not reoccur have been removed. A full version of this model map can be seen in the Appendix.

The iterated model components make up 26 of the 53 total considered model components in this team's solution. Two of these model components, the Arrhenius Equation and the material balance, appear together in Team A's predictive model. The others include design strategy considerations (design of experiments), a simple relationship the team recognized as most useful for end-project optimization (thickness is linear with time) and a calculation for one of their project metrics (utilization).

Table 2. Iterated Model Component Identities

Model Component Letter	Model Component Identity
A	Design of Experiments
B	Thickness is Linear with Time
C	Uniformity Increases as Temperature Decreases
D	Diffusion Control vs Reaction Control
E	Material Balance
F	Utilization

Motivation for Iteration

When considering the motivation to create and revise model components, John Clement observed small modeling episodes triggered by "dissatisfaction". This dissatisfaction, or dissonance, was defined as "an internal sense of disparity between an existing conception and some other entity. This can occur at mild, as well as strong levels, as opposed to the concept of 'conflict,' which suggests only a strong disparity."[4] This dissatisfaction can also come from a gap in understanding as opposed to an outright conflict.

Team A seemed to be motivated through small episodes of dissatisfaction. There were three dissatisfaction triggers observed: Gaps in knowledge, gaps in existing model components, experimental data cues, and meeting cues. In total, there were 19 episodes of dissatisfaction and 16 of them lead to the generation or evaluation stage of model iteration. The other three episodes lead to the use and revision stages of model iteration.

In the Arrhenius equation example above, the initial model generation is caused by a gap in knowledge with regards to their understanding of temperature and flow rate. The next instance of the Arrhenius equation appears after the team's first run and is triggered by their efforts to use the data they obtained from that run. When creating the predictive model, the Arrhenius equation was integrated to essentially fill a gap present in their current model of the system. Finally, the notion of finding an empirical value of activation energy was cued during their second meeting with the coach.

Information Applied in Modeling Efforts

As is common with all types of laboratories, Team A utilizes their experimental run data to assist in their modeling effort. In the example above, several experimental runs are specifically tailored to help them obtain data necessary to calculate a value for activation energy. During this project, the team also drew from outside resources when their own understanding of the project was not sufficient. In the case of Team A, this took four forms: literature search, academic experience, professional experience, and inter-team validation.

The literature search tends to occur near the beginning of student projects. In their literature search, Team A come across a website that allows them to run a simulation of a small-scale reactor. Through a short round of experiments, they are able to determine the relationship between thickness and time.

> **Student 1**: This is for their particular testing, maybe they are offering testing to people
> **Student 2**: But that is for 1 wafer run for half an hour.
> **Student 1**: We don't need to look at what other people charge, we need to look at what we're getting charged. Basically we need to figure out how many runs we expect to do before we figure out how many measurement we're going to do. And then we need to multiple that by $5000 to come up with our budget.
> **Student 2**: OK, so let's try maybe 100
> **Student 1**: I am trying to and it is not letting me, I don't know if it is not something you can change. All this stuff is acting like you can't change it. But that is ok, I was just curious how it changed that. Let's change the thickness and see what happens. So if you want to double the thickness, same wafer same size you end up with double the time. So according to this there is a linear deposition reaction thing that happens because that is like exactly double.
> **Student 2**: Yes
> **Student 1**: So I will write that down like.
> **Student 2**: Double thickness double time?

Sources for this team included websites, books, and various journal articles. Interestingly, many of the resources utilized by this team went undocumented in their notebook and memoranda despite the fact that small bits of information from these sources end up providing assistance in the project.

Academic experience plays an important role in this project as it is designed to serve as a capstone course. In some cases, the students know what they want to do, but do not realized the connection between that process and their academic training. In others, like the Arrhenius equation example above, the student team has a clear picture of the idea. The open ended nature of the project allows for different unique solution pathways which can all draw from different portions of a student's academic knowledge.

Though it does not appear in the discourse related to Team A's recurring model components, one of the team members drew upon industrial internship experience to inform the team at various points in the project. Even for students that do not have prior industry experience, their decisions are often made with respect to expected industry behavior. Student teams also interact with one another. This communication can range from gauging relative progress to the exchange of information regarding an approach to the project.

> **Student 1**: 0.2141? 83%
> **Student 3**: Not bad
> **Student 1**: I don't know, I want to find out from the other people. What did you guys get for utilization?
> **Other group**: What

Student 1: What kinds of utilizations are you getting?
Other group: utilizations?
Student 1: It goes on both sides. It's all about how much you let to the atmosphere
Other group: So we did it and I think we came up with
Student 1: Don't you have 1 utilization for every run?
Other group: Ok
Student 3: It's how many mols you need divided by how many mols you pumped into the machine
Other group: ok
Student 1: So are you getting like 10, 90? What are you getting?
Other group: I have no idea.
Student 3: That's not bad for a first run. I actually start heading out to polymers, will you email that to me? That excel document?

Team A often reached out to other teams for the former reason: relative progress reports. When they first complete a calculation related to a project metric (utilization, expressed as a percentage), they immediately seek to gauge their progress with a nearby team. In this instance, the team did not have useful input, but students from Team A frequently make statements similar to "I wish I knew how far other groups were."

VII. Conclusions and Implications

One team's modeling behavior through their progress in an authentic engineering task has been characterized through an analysis of their work products and meeting transcripts. In analyzing instances of modeling, cycles of model iteration (generation, evaluation, use, revision, confirmation, and rejection) were observed.

We provided a detailed example of model iteration in Team A's development of the Arrhenius equation. In the five times the team engages the Arrhenius equation, their development moves from a vague understanding of the base form of the equation to a more fully understood model component situated within the context of a larger predictive model.

Student motivation tended to be driven by "dissatisfaction episodes". Some of these episodes were driven by the recognition of gaps in their knowledge, such as the recognition of their lack of understanding regarding temperature that initially generated the model. Other dissatisfaction episodes revolved around contact with their project coach, in this case that sparked work toward an empirically derived value of the activation energy. In a later episode, a change to the Arrhenius equation model component came from the empirical data that defined the change in activation energy.

As work in this field progresses, the characterization of dissatisfaction episodes can assist in the design of learning systems that promote modeling behavior. In future work, more teams will be added to this characterization and a typology of dissatisfaction episodes can be developed.

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Appendix

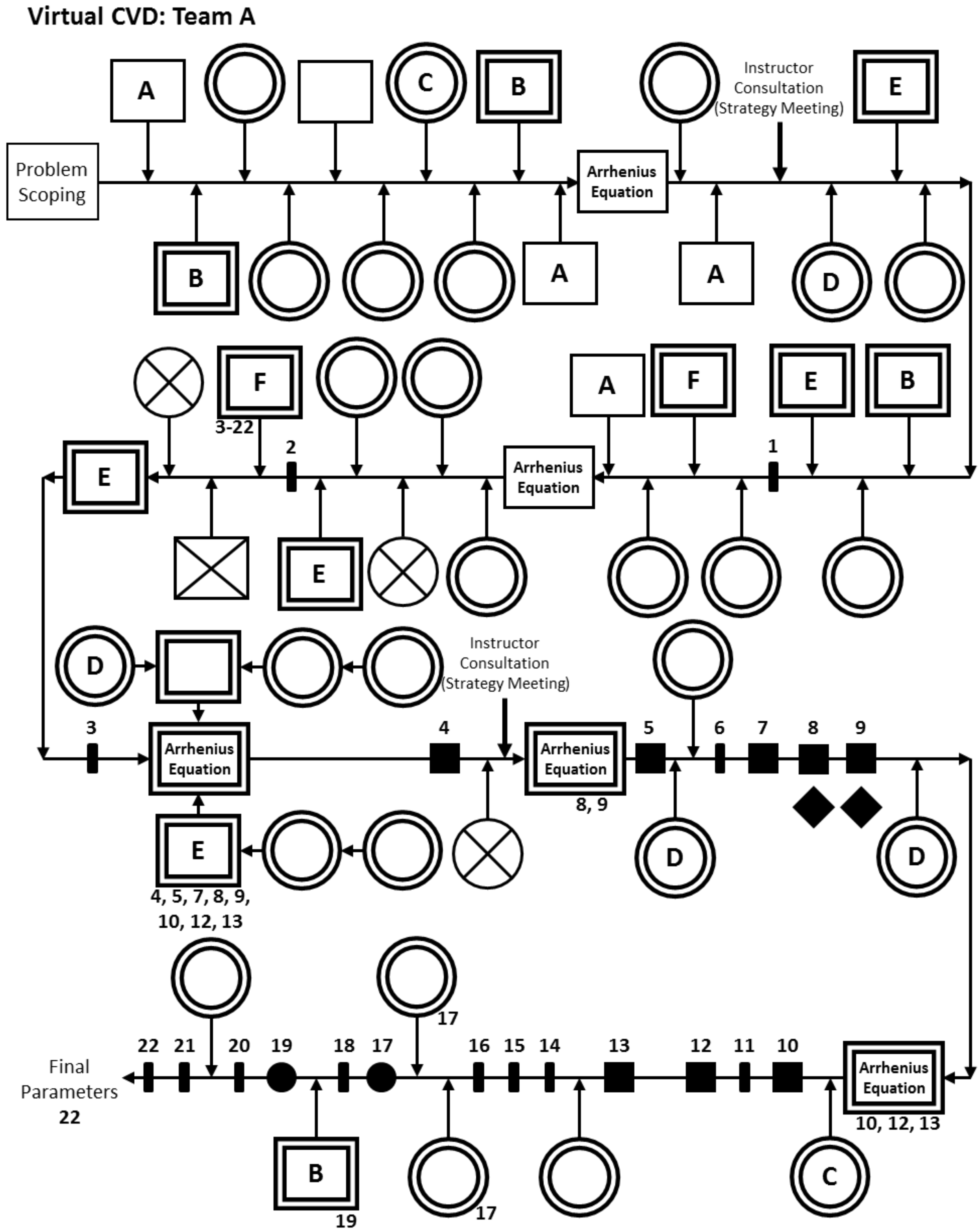

Figure A. Full Transcript-Based Model Map for Team A. Iterated model components are identified with unique letters. Blank model components are unique from one another.