Student Learning in
INDUSTRIALLY SITUATED VIRTUAL LABORATORIES

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The undergraduate laboratory plays a pivotal role in science and engineering curricula.[1,2] Traditional physical laboratories are resource intensive, however, and due to these constraints, do not always achieve their diverse set of intended learning outcomes. One way to overcome these limitations is to use alternative modes of delivery, such as virtual or remote laboratories.[3] In a virtual laboratory, students do not interact with real equipment to obtain data, but rather with computer simulations of laboratory or industrial process equipment that produce results that can be obscured by pre-programmed statistical variation.

In the most common approach, the virtual laboratory is used as an alternative mode and simulates a similar set of activities as in the corresponding physical laboratory at the university.[4-7] In a few cases, virtual laboratories have been used to create learning activities with no analog to the university instructional laboratory.[8,9] The instructional and software design of the virtual laboratories described in this study fall into the latter case and are based on the situated context of a practicing engineer in industry. The virtual laboratory project is structured around the task of having students determine the operating parameters for chemical processes for volume production through experimental design, interpretation, and iteration. In this sense, the virtual laboratory project simulates what expert engineers do in practice, and ends up very different in character than the physical laboratory at the university.

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The virtual laboratory functions similarly to pedagogies described by problem-based learning,[10,11] model-eliciting activities,[12] and context-rich problems.[13] Like these pedagogies, a complex, ill-structured, open-ended, authentic problem forms the context for learning, and students actively and collaboratively engage in the solution. The environment also requires students to greatly extend their personal responsibility for learning. In the case of the virtual laboratory, however, the data are generated dynamically by the software based on each student team's distinct choices of reactor parameters and measurements, as opposed to having the instructor provide static data sets. Therefore, not only is the solution path unique for each group, but the data that are used to find that solution are also unique.

Shavelson, et al.'s,[14] cognitive framework is used to investigate student learning in the virtual laboratory environment. This framework describes scientific achievement as consisting of four types of knowledge: declarative ("knowing that"), procedural ("knowing how"), schematic ("knowing why"), and strategic ("knowing when, where, and how our knowledge applies"). Schematic knowledge includes principles, schemas, and mental models that explain the physical world. Strategic knowledge is demonstrated by determining how and what knowledge applies to a new situation and includes domain-specific conditional knowledge and strategies such as troubleshooting and problem-solving as well as monitoring.[15] Although laboratory experiences are meant to draw upon and develop all four types of knowledge, often the physical laboratory at the university relies upon the declarative and procedural aspects of recall of facts and adherence to proper protocol. In the virtual laboratories, however, the physical component is removed and students are able to focus on developing schematic knowledge, by integrating concepts and building models, and strategic knowledge, by intelligently combining these models to formulate a solution to an ill-structured and open-ended task.

This paper provides an overview to the instructional design of the virtual laboratory project as it has evolved over the past six years. This description is followed by presentation of the three major research methods that have been used to investigate student cognition, metacognition, and social interactions in this environment, and a summary of some of the research findings from each method. The research aims to provide greater understanding of student learning in this environment. This understanding is needed for more systematic software development and instructional design, application to other engineering processes, and widespread use. With a clearer understanding of the cognitions and social interactions of students, the role of virtual laboratories in the curriculum and in accreditation processes can be explicitly identified.

INSTRUCTIONAL DESIGN

Two virtual laboratories have been developed: a Virtual Chemical Vapor Deposition (VCVD) Laboratory and a Virtual Bioreactor (VBioR) Laboratory. Screenshots of the three-dimensional student interfaces for each virtual laboratory are shown in Figure 1. The instructional design is "industrially situated" both in the scale of the process and by the nature of the engineering task that student teams complete. The VCVD Laboratory simulates an industrial-scaled vertical chemical vapor deposition reactor in which silicon nitride is deposited from dichlorosilane and ammonia gases at low pressure and high temperature. Students are tasked with achieving maximum thickness uniformity and minimum dichlorosilane utilization by adjusting operating parameters including gas feed rates, temperatures of five reactor zones, system pressure, and duration of operation. The VBioR Laboratory is based on an industrial stirred-tank fed-batch bioreactor, and can be used for different applications, such as production of a recombinant protein or degradation of waste, and run in either batch or fed-batch mode. Students aim to achieve maximum volumetric productivity by varying input parameters such as temperature, substrate concentrations, cultivation times, and feed flow rate. Random process and measurement variation is added to the data for students from the simulation output. In both of these virtual laboratories, the students are experiencing industrial aspects of engineering that they typically do not experience in university classes and laboratories. The details of the VCVD and VBioR Laboratories have been previously published.[16-18]

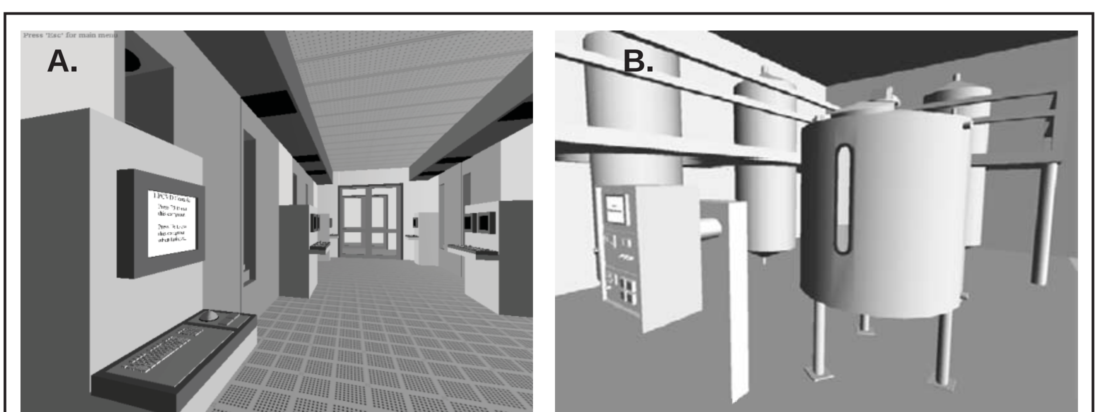


Figure 1. *Screenshots of the student interfaces: A. The Virtual CVD laboratory and B. The Virtual BioR Laboratory.*

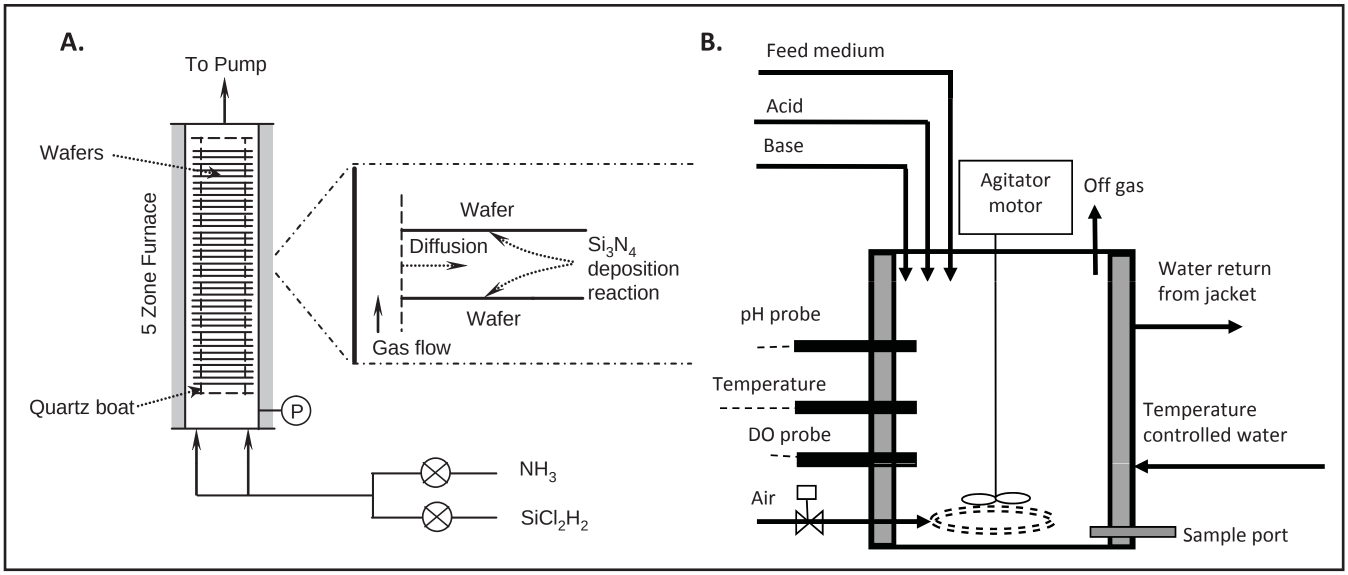


Figure 2. *Schematic of the equipment simulated by the two virtual laboratories: A. chemical vapor deposition reactor and B. bioreactor.*

Although centered in different domains, both the Virtual CVD and Virtual BioR laboratories have at their root reaction kinetics and material balances. Schematics of the simulated systems are indicated in Figure 2. The VCVD system can be described using a simulation with transient solid phase accumulation, and a pseudo-steady state gas phase. The VBioR is an inherently transient system, with cell growth, substrate consumption, and product synthesis and degradation occurring throughout the cultivation. Both scenarios present an adequate challenge to students while eliciting the use of engineering principles and models.

The instructional activities are constructed around principles of scaffolding, coaching, reflection, articulation, and exploration.[19] The group-based project tasks teams to develop a *process recipe* (*i.e.*, values for reactor parameters) for release to high-volume manufacturing, by:

- *Composing an* experimental design strategy memorandum *and reviewing it with the instructor before accessing the virtual laboratory. (reflection-on-action activity);*
- *Recording activity in an* experimental journal*, keeping track of the run parameters, data analysis, interpretation, and conclusions and decisions from the interpretation. (reflection-in-action activity);*
- *Preparing an* update memorandum *and reviewing it with the instructor one week after having access to the virtual laboratory and revising experimental design (reflection-on-action activity); and*
- *Synthesizing experimental results in the form of a final* written and oral report.

Consider two central learning events that occur in partnership with the software: (1) as the students prepare to engage in the virtual laboratory and (2) when they respond to the data that is dynamically generated. Both require a transition from schematic knowledge to strategic knowledge. In both cases, the learning does not occur directly within the software interface; rather, students need to engage at a range of cognitive activities, from anticipating data from planned experiment trials to sequencing runs, from evaluating data to linking data patterns to parameters that need to be changed.

The beginning of the project directs students to an information gathering/problem scoping phase that places unusual responsibility on the students themselves to formulate the problem. This formulation is structured around a 20- to 30-minute design meeting with the student team and a faculty instructor, the domain expert who acts in the role of manager and coach. In this role, the instructor reinforces the epistemic frame of the engineering profession by modeling the way an engineer thinks and acts.[20] At this meeting, the students must deliver a memorandum that specifies the parameters for their first "run," a strategy for subsequent runs, the approach to evaluate the experimental data from the runs, and a virtual budget. In pursuing their design strategy, students both search the literature to obtain reasonable reactor parameters and integrate prior knowledge from a diverse set of courses ranging from material balances and reaction kinetics to applied statistics and experimental design. Developing a project budget motivates the teams to consider the entire project scope (*e.g.*, the number of runs and measurements that are needed), situates the problem in the context of engineering practice, and provides an urgency for students to be thoughtful and efficient in experimental design. During the meeting, the instructor provides feedback by asking questions to guide the students in developing features of the strategy, initial parameters, and budget that they have not appropriately addressed. Only after the team has an acceptable design (typically after a revision) are they given access to the virtual laboratory. Both the design meeting and the following intermediate update meeting

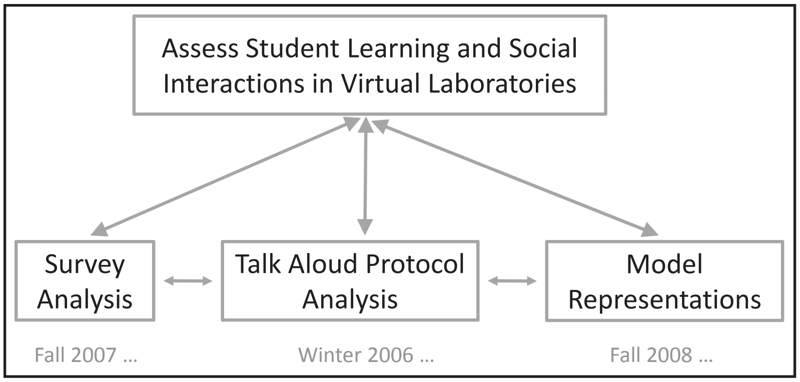


Figure 3. *Research methods to assess student perceptions and learning in the virtual laboratories.*

provide rich opportunities for reflection-on-action, which can result in improvements to the experimental approach and promote a deeper understanding of the process.[21]

A second primary learning mechanism occurs throughout the bulk of the project when students obtain the output data generated by their virtual experiment at the run conditions that they have chosen. When they perform an experiment and obtain data, the student teams must confront what they actually obtained vs. what they expected (or did not consider). We have noticed resulting cases of cognitive conflict and cognitive confirmation. Posner, et al.'s,[22] model proposes that conflict caused by anomalous data is a necessary first step to achieving conceptual change. It is believed significant learning occurs during the time when the students are trying to make sense of their data and trying to make decisions about what input parameters to try during their next run; however, more research is needed to elucidate the specific nature of the student cognition.

RESEARCH QUESTIONS AND METHODS

The mixed methodological basis of this research is grounded in a phenomenological perspective of ascertaining how students who are engaged in the virtual laboratory as a learning environment make sense of their experiences; how they operationalize their schematic and strategic knowledge; and how their cognitions manifest and the degree to which the cognitions are distributed. Specific research questions include:

1. *What is the nature of the experimental design process that students apply in the virtual laboratories?*
2. *How does students' tolerance for ambiguity change while completing the virtual laboratories?*
3. *In what ways do students perceive the virtual laboratories as an authentic experience that is reflective of real-life engineering? How do the ways that students perceive virtual laboratories compare to physical laboratories?*
4. *What types of knowledge structures and cognitions are demonstrated by students when engaging with the virtual laboratories?*

Figure 3 shows the primary research methods that have been used in our research: survey analysis, talk-aloud protocol analysis, and model representation and usage maps. These methods do not align solely to a specific research question, but rather can be analyzed through different lenses to address the four research questions. Having multiple data sources for each research question allows triangulation of results and testing of alternative explanations to ensure research rigor.[23] The theoretical framework is based on a multi-tier teaching experiment design that is used both to assess iteratively the knowledge structures evoked by students engaged in the virtual laboratory experiments and to improve systematically the instructional design.[24] Rather than pre- and post-test design, this approach is to generate audit trails that reveal important and in-depth information about the nature of learning and development that occurs.

SURVEY ANALYSIS

A set of free response survey questions has been posed to students in the first term of the capstone Senior Laboratory class in which the virtual laboratory project is delivered. This method seeks to identify how students' perceptions of their knowledge and awareness of their own learning evolve as they move through the three structured laboratory experiences in that class. The first and third laboratories are physical laboratories, based on the unit processes of heat exchange and ion exchange. The second is the virtual laboratory. Students' perceptions of learning provide a lens into their metacognitive processes. Metacognition is the process of students monitoring their own learning and is an important element of student learning in the engineering context.[25] Student understanding of the goals of learning experiences is a critical element in student acquisition of the content understanding and deep cognitive and procedural skill development in higher education.[26]

The survey questions were asked after each of the three laboratories as soon as possible after submission of the final laboratory report for that given laboratory. There were, in some cases, overlaps with content presentation for the next laboratory. The following questions were coded and analyzed:

Q1. What do you think the instructors intended you to learn by doing the (Ion Exchange/Virtual/Heat Exchange) laboratory?

Q2. How would you explain this laboratory experience to a first-year student?

Q3. When you close your eyes and picture the lab experiment, what do you see?

The course performance of students, measured by the weighted final score on all assignments, was used to correlate aggregate responses to performance. The survey has been administered for the past three years. To date, a total of 999 student responses have been coded. The student responses were anonymous, and responses to all three laboratories were only analyzed after the course was complete.

The coding method for responses was developed as follows. The raw data were analyzed by content analysis to establish categories to group the responses.[27] The number of coded statements in each category was summed across all of the student surveys for each of three researchers for each of the three laboratories. To achieve adequate interrater reliability, the following process was used. The three faculty researchers met together and the independently coded responses were compared and the differences reconciled. To determine the validity and reliability, two other researchers with no connection to the project were given a subset of 60 responses from one of the survey questions (20 responses per question per laboratory). This subset of responses was randomized among the three laboratories, so the researchers could not identify what response was associated with what laboratory. The two researchers went through the same process of individually coding and then reconciling the data. The value of interrater reliability using the Cohen's Kappa (κ) statistic was 0.89. The fact that the second group had randomized responses suggests that there is not a bias based on the laboratory. Statistically significant categories of the nonparametric, ordinal coded response data to the survey questions were determined using the Pearson chi-square test.

A sample response to survey Question 1 for the Virtual Laboratory project follows:

> *"I believe the instructors wanted us to experience how lab work is and should be performed in the real world. We did not have to worry about actual lab procedures, so experimental design and analysis were the focal points of the lab. We had the added constraint of a budget, which made proper experimental design key, since we could not overcome problems created by collecting data from poorly planned experiments by running the experiment many times and collecting lots of data to get it right. I think they also wanted us to work on the process of looking at the theory behind the lab first to get an idea of where to start our experiments, and then perform intermediate data analysis to determine best course for future experiments as more information became known."*

This response was rated as higher-order cognition, and rated in the following categories: experimental design, critical thinking, and situated nature. Further details of this analysis are presented elsewhere.[28,29]

Analysis of the complete set of survey responses shows enhanced awareness of experimental design, a greater reference to critical thinking, and more responses rated at higher-order cognition in the virtual laboratory, and an enhanced awareness of laboratory protocol in the physical laboratories. The sum of high-cognition rated statements for the three laboratories correlated with student overall performance in the course.

It is believed significant learning occurs during the time when students are trying to make sense of their data and trying to make decisions about what input parameters to try during their next run....

There is growing tolerance for ambiguity as students move through the course and a shift from a perception of ambiguity in the instruction and instructors' expectations to an ambiguity in the experimental process itself. There is indication, however, that a significant portion of students may not view the virtual laboratory as a real system. Even with limitations in the physical presence induced by the software interface, many students have indicated an ability to suspend disbelief and demonstrate psychological immersion in the virtual laboratory project. There is evidence that cognitive partnerships are formed between students and the virtual laboratory artifact, characteristic of a rich learning experience.

TALK-ALOUD PROTOCOL ANALYSIS

Protocol analysis consists of audio recording selected student teams while they "talk aloud" as they solve the virtual laboratory project. Protocol analysis has been shown to give insight into cognitive processes, especially in situations where higher-order critical thinking ability is needed.[3,30] In the virtual laboratory project, analysis of the talk-aloud data can provide information about the nature of the iterative experimental design process, how models are developed and the knowledge structures used, the nature of the feedback in the design and update meetings, the team's tolerance for ambiguity, the effect that the team dynamic has on the project direction, and instances in which cognition is distributed through cognitive partnerships.

Over the span of five years, complete data sets have been audio recorded from 16 student teams as they have completed the virtual laboratory project (12 CVD and four BioR). The method we have developed follows. The researcher observes and audio records the teams at all times they work on the project, which has averaged approximately 20 hours. To the extent possible, recording occurs at all times the teams are engaged in the project, from problem scoping to their final oral presentation. During data collection, students are instructed to verbalize their thoughts, but not encouraged to describe or explain their thoughts. As the students proceed, the researcher fills out a data sheet. This data sheet has been specifically designed to align with the qualitative analysis method in several ways.[31] The right side of the data sheet contains a table where observed tasks are chunked into the design processes and the quality is evaluated according to a rubric we have developed. Significant sociocognitive interactions that impact the completion of the task are noted. On the left side of the data sheet a task map visually depicts the flow of tasks. The "tolerance for ambiguity" demonstrated by the team during the session is quantified as rated according to Perry's[32] empirical model with nine levels of intellectual growth. The data are then transcribed for more fine-grained analysis.

We have identified a set of performance tasks in which the students engage as they complete this situated project. An example of this analysis is shown in Figure 4, which depicts the experimental pathways taken by a student team. The sequence of tasks completed by the teams is indicated in numerical sequence in the pathway. Inspection shows the team achieved many iterative cycles, completing three design cycles (outer loop), 11 analysis cycles (inner loop), and one Design of Experiments (tasks 26-33). Similarly, results from the task analysis from the other teams participating in the think-aloud sessions have been compiled.[16, 31] In all cases, the teams demonstrated an iterative approach to experimental design, completing an average of three design loops and 12 analysis loops. This evidence suggests that students were engaged in the intended approach of experimental design.

The modified Perry's levels were applied to quantify the teams' tolerance for ambiguity. Evaluation results elucidating tolerance for ambiguity indicate that by completing this open-ended problem most students evolve past "blind acceptance of authority" and become aware of a "multiplicity of views"; however, while some teams continued to climb Perry's levels, eventually becoming comfortable with the idea of "contextual relativism," other students did not.[31] An interesting parallel to these differences is found in the nature of the sociocognitive interactions found in the different student teams; these interactions seem to be able to either promote the desired learning, or they can be detrimental to the intended learning outcomes.

MODEL REPRESENTATION AND USAGE MAPS

To capture the model construction and higher cognition and to characterize the schematic and strategic knowledge invoked by the virtual laboratory project, we have developed Model Development and Usage Representations (Model Representations) as an analysis tool. The Model Representations are generated from student work products, such as journals/laboratory notebooks, written reports, and memorandums, and from the instructor interface, which records all groups' run parameters and results. They are a visual and chronological coding tool used to identify and characterize student knowledge structures and cognition as students perform the virtual laboratory project. The Model Representations can be used to identify the ways students use their schematic knowledge to build models and use their strategic knowledge to integrate these models into their project solutions.

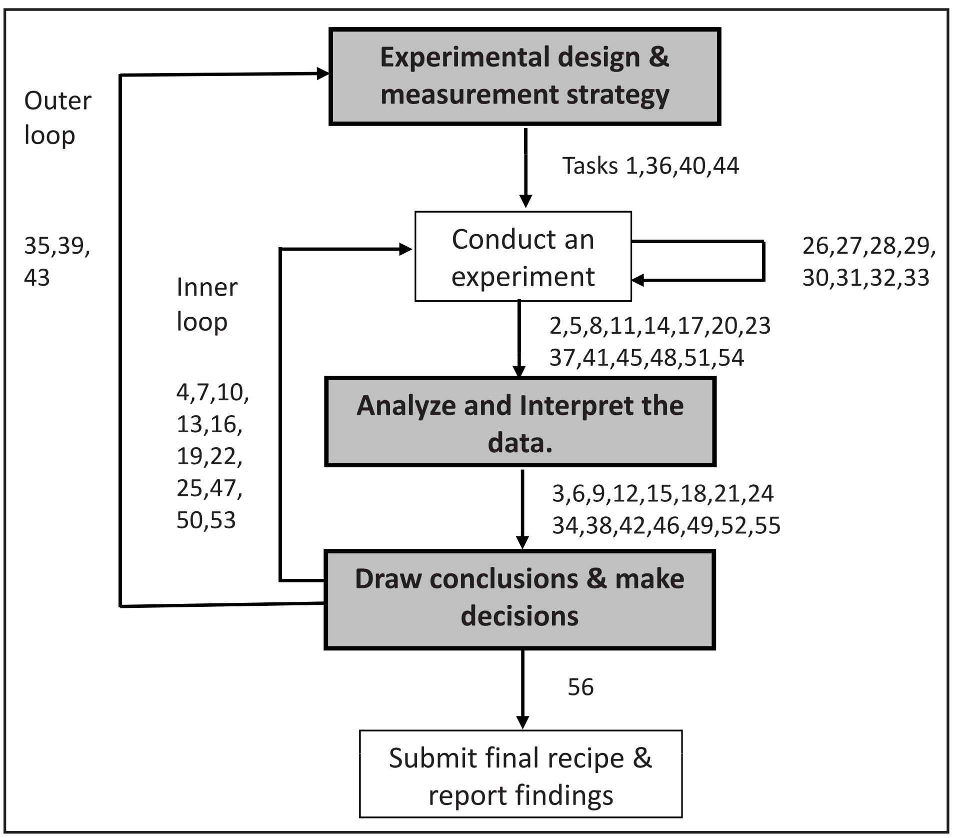


Figure 4. *Experimental paths derived from task analysis of one team that participated in the "talk-aloud" study.*

Student journals serve as the primary source of information for coding since they are intended to contain all references, notes, results, and calculations over the course of the project. Model components are identified from the student journals chronologically and are then supplemented with information from other sources that serve to confirm, explain, or expand upon the journal content. Student researchers first individually dissect the work products to construct the preliminary Model Representation. Consensus is then obtained by a group of two students and two faculty. One faculty member—the domain expert in the appropriate field—examines the source material and evaluates the accuracy and context of the Model Representation. An Overview statement is then written that summarizes in

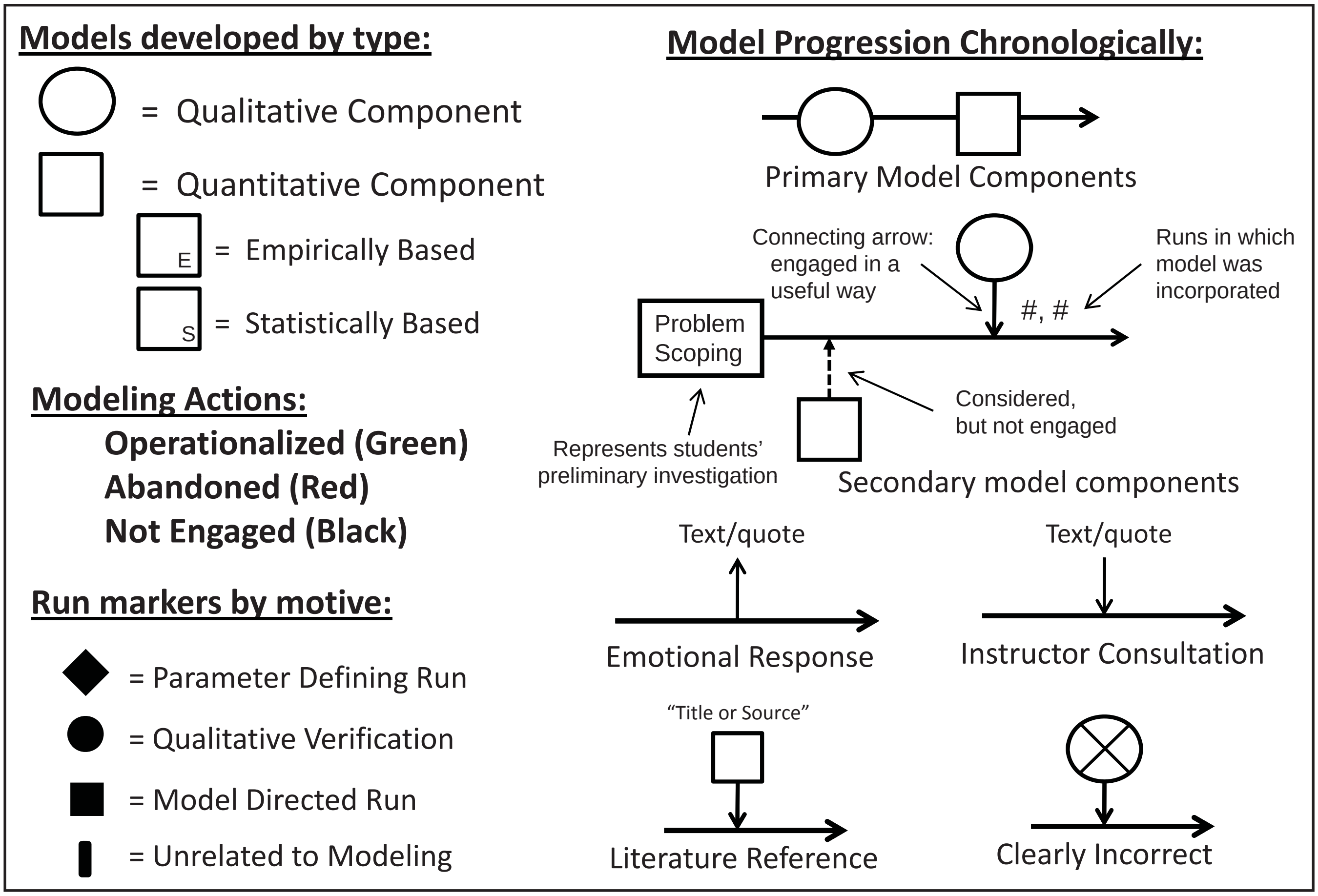


Figure 5. *A summary of the Model Representation component key.*

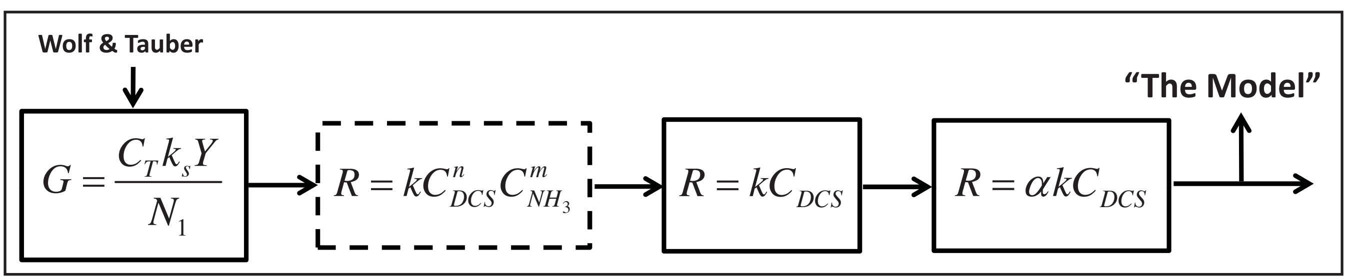


Figure 6. *Progression of the kinetics model component through the project for CVD Team I.*

a concise manner the group's approach and integration of model components in its unique solution to this authentic, ill-structured problem. To assure reliability of coding between the Model Representations of the two virtual laboratories, the student and faculty who analyze the other virtual laboratory participate in this process. A more complete description of the methodology for developing Model Representations is presented elsewhere.[33]

Figure 5 shows a summary of the coding key that has been developed. Model Representations specify the types of model components employed (quantitative or 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 combined along a timeline with experimental runs, emotional responses, and instructor interaction to show context and form the complete Model Representation.

To illustrate the effectiveness of Model Representations as a tool to study student learning, a subset from one Virtual CVD Laboratory group (CVD Team I) is presented in Figure 6 showing the progression of the kinetics model component through the project. As illustrated in the first box from the left, the team started by using a form of the first order rate law found in a common textbook in silicon processing[34]; however, they did not explicitly recognize it as a first order rate law. The group then replaced this expression with a more complex, higher-order rate equation that they were simultaneously covering in their reactors class. They were unable to solve for the higher-order rate parameters using the complex data sets generated from their runs and measurements. Consequently, they abandoned this approach (as illustrated by the dashed line in Figure 6 or a red line in Figure 7). They then simplified the expression to a pseudo-first order rate equation (third box from left). This form was utilized with an empirical correction factor in this team's progression towards final parameters (fourth box). Integration of other model components (including a material balance and the Arrhenius relationship) led to what the team anthropomorphically called "The Model," which was used to predict run parameters to converge on the process recipe. The progression of this model component is reflective of deep learning and shows characteristic adaptability of experts. This group was rated as *high* for their use of *schematic knowledge* in developing the model and *high* for their use of *strategic knowledge* in operationalizing the model effectively to obtain a useful solution.

A total of 27 Model Representations have been completed for the 2008 cohort in the capstone laboratory course at Oregon State University and four examples are presented in Figure 7. This figure places the Model Representations on axes of schematic and strategic knowledge. The complete model representation for CVD Team I is shown in the upper right as high schematic and high strategic. The different model components are illustrated with respect to the 17 runs the team performed using the component key shown in Figure 5. Similarly the other 26 teams were rated on use of schematic and strategic knowledge. Examples of teams rated as high-strategic, low-schematic (Team II); high-schematic, low-strategic (Team IV); and low-schematic, low-strategic (Team III) are shown. Inspection of Figure 7 shows the wide range and variety of model development approaches in solving this authentic, ill-structured problem.

Team IV showed sound schematic knowledge and engineering skill using a model-based approach, and attained high uniformity after just four runs. Their strategic knowledge was insufficient to respond to a special cause of variation or to determine a meaningful end point to the project, however. Interestingly, failure to identify a reasonable end point was followed by largely incorrect methods, which later yielded to empirical adjustments. Conversely, Team II's schematic knowledge is incomplete and demonstrates misconceptions. For example, their value for activation energy is originally inaccurate, due to an incorrect application of a model. The unreasonable value is recognized, however, and the value is quickly changed to a value from the patent literature (good strategic thinking), which is central to the team's solution.

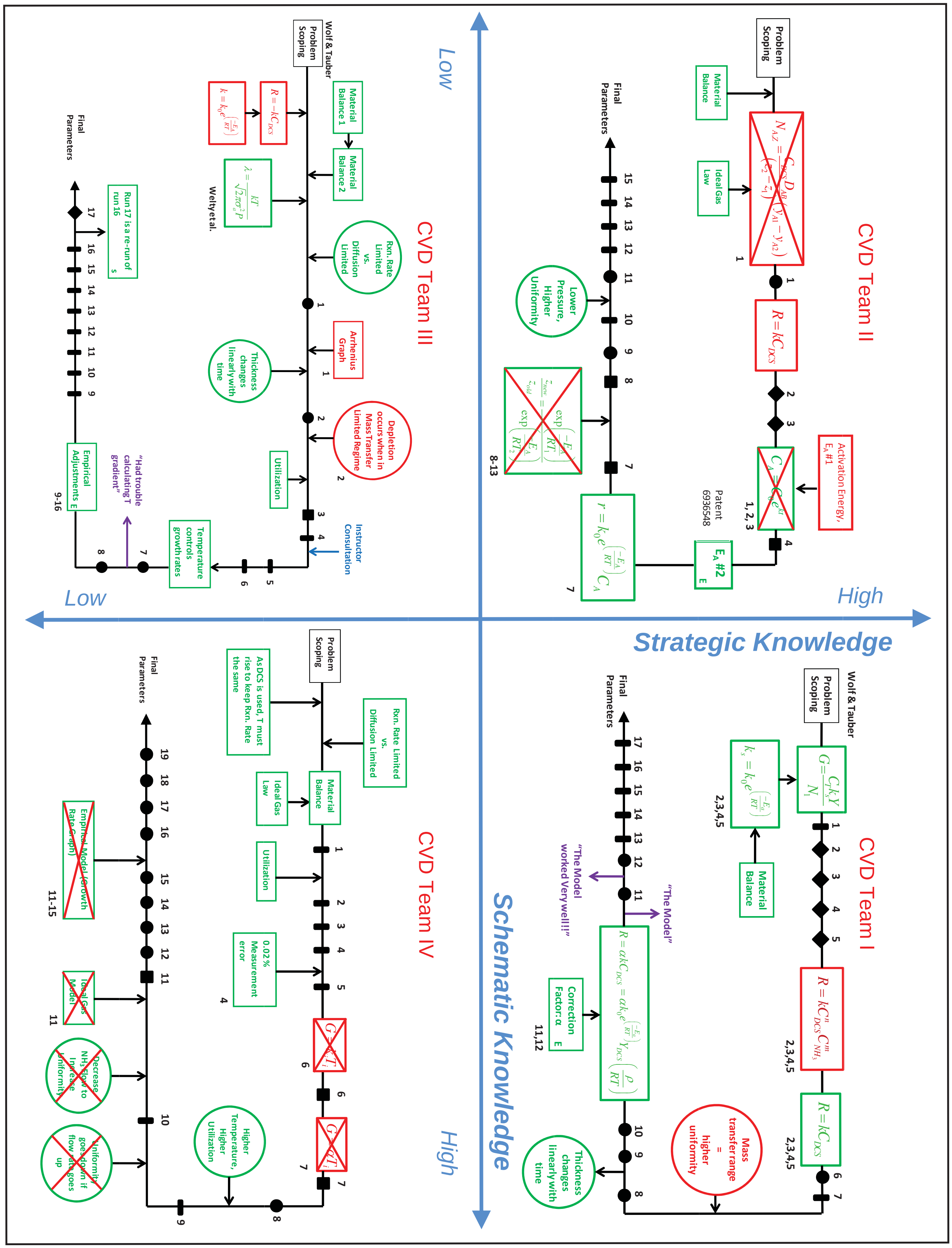
The Model Representations indicate learning may be occurring across the spectrum of quality of knowledge structures. For example, consider Team III (low-schematic, low-strategic). Initially, their methods appear to consist of randomly responding to cues within the problem without any evidence of drawing from a knowledge framework. As illustrated in the top line of the Model Representation, many methods from different classes are attempted. Run 6, however, allows the group to identify a core concept and integrate it into the project. This guides their future efforts. All run input parameters prior to run 6 used a gradient in temperature, and the group had trouble simultaneously considering both the kinetic influence of temperature and the influence of gas flow rate on reactant depletion. In run 6, zone temperatures were constant throughout the reactor. At this point the team identified that "decreasing growth rate up the tower (sic) is due to decreasing concentration." While the team showed low schematic and strategic knowledge, the experience of Run 6 enabled a transformation in their solution process (see bottom line vs. top line of the Model Representation). This transformation may indicate genuine change of the students' conceptual understanding, but other explanations are also plausible and this aspect needs to be more carefully studied. We believe traditional curricula characterized by fragmented courses emphasizing contrived end-of-chapter type calculations may contribute to the lack of coherence in knowledge structures.

CONCLUSIONS

The following major conclusions have been found from this research on student learning in industrially situated virtual laboratories:

- *Virtual Laboratories can provide a dynamic Problem-Based Learning experience where students engage in an authentic industrially situated task.*
- *Data analysis shows that students exhibit the intended iterative experimental design process and exhibit greater references to critical thinking and higher-order cognition in the virtual laboratories than in capstone physical laboratories.*
- *Evidence suggests that the students' tolerance for ambiguity is developed as students move through the project. Additionally, there is a shift from a perception of ambiguity in the instruction and instructors' expectations to an ambiguity in the experimental process itself.*
- *A significant portion of students may not achieve physical presence and view the virtual laboratory as a real system. Many demonstrate the ability to suspend disbelief leading to psychological immersion, however. In some cases, a clear cognitive partnership between the students and the virtual laboratory artifact is demonstrated.*
- *Cognitive historical analysis of work products shows a diverse set of modeling approaches in the student solutions to the virtual laboratory project. This method shows promise for discriminating between widely varying the schematic and strategic knowledge structures of the teams.*

Figure 7 (facing page)*. Four model representations placed in reference to evaluation of schematic knowledge (x-axis) and strategic knowledge (y-axis) demonstrated.*



CVD Team I
CVD Team II
CVD Team III
CVD Team IV
Strategic Knowledge
Schematic Knowledge
Low
High
Low
High
Problem Scoping
Wolf & Tauber
Material Balance
Ideal Gas Law
Final Parameters
Activation Energy, E_A #1
E_A #2
Patent 6936548
Lower Pressure, Higher Uniformity
Thickness changes linearly with time
Mass transfer range = higher uniformity
Correction Factor: α
"The Model"
"The Model worked very well!!"
Material Balance 1
Material Balance 2
Weltyetal.
Rxn. Rate Limited vs. Diffusion Limited
Arrhenius Graph
Depletion occurs when in Mass Transfer Limited Regime
Utilization
Instructor Consultation
Temperature controls growth rates
"Had trouble calculating T gradient"
Empirical Adjustments
Run 17 is a re-run of run 16
As DCS is used, T must rise to keep Rxn. Rate the same
0.02% Measurement error
Higher Temperature, Higher Utilization
Empirical Model (Growth Rate Graph)
Ideal Gas Model
Decrease NH_3 flow to increase uniformity
Uniformity goes down if flow rate goes up

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