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Participation and Learning in Labs Before and During a Pandemic

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Participation and Learning in Labs Before and During a Pandemic

Abstract

Experiments form the backbone of much of engineering education, but because it is not always possible to do them in person, simulations can provide a powerful alternative to assist student learning. We present data from two versions of two chemical engineering courses where in-person labs pivoted to virtual simulated experiments. In the first-year introduction to chemical engineering course we designed a simulation for students to design and then test a bench-scale prototype of a remediation column for acid mine drainage. In the junior-level chemical engineering laboratory—students typically carry out a bomb calorimetry experiment of sucrose and then analyze their data. We created a simulation based on a combination of thermodynamic models and previous years' data. We found that opportunities for learning came out of the amount of agency and the consequential decisions each experiment allowed the students to make. Based on student engagement and learning, we propose guidelines for integrating simulations as prelab activities.

Introduction and research purpose

Laboratory experiments and the practical experience they provide for students are a vital part of engineering education. When such in-person and high-contact learning is not possible (as amidst the COVID-19 pandemic) it is tempting to assume that there are not valuable and viable alternatives. However, that does not mitigate their importance to the learning of students, nor should the students go without. In this paper, we investigate two variants of simulations used in place of in-person labs. Specifically, we contrast student engagement and learning across the face-to-face and simulation versions to identify aspects of these experiences that supported students to make consequential decisions and develop a sense of ownership over the methods of experimentation, methods of analysis, interpretation, and conclusions. We therefore sought to answer the following research questions:

- What kinds of decisions did students make in the lab (both in-person and simulated)?
- To what extent did students show ownership over the experimental methods, analytical methods, and their interpretation of the results?

Theoretical Framework

Many studies have contrasted face-to-face and simulated laboratory experiments, and investigated variants of simulations that support learning. To make progress on our study aims, we orient our work around agency and ownership, and specifically, the idea of framing agency, which argues that students should make decisions that are consequential to the problem frame. While typically a focus of design projects, we situate framing agency in laboratory and experimental design.

What is framing agency and how does it relate to learning and ownership?

Design—including experimental design—is centered around the idea of ill-structuredness. Ill-structured problems, rather than having one right answer and one path to achieving that answer , have multiple solutions and multiple paths to those solutions [1]. Because design problems are not linear like more canonical problems, design problems must be framed and reframed by the designer throughout the process to achieve success. Problem framing is endemic to design [2] and involves both understanding and defining the scope of the problem. The process of problem framing is consequential not only for the problem itself (effecting the resulting design by deciding what is important or must be focused on) but for the designer personally, as the designer learns and interprets information based on their experience [3]. Thus problem framing includes *agency*, or the ability and empowerment to make decisions.

The ability to make decisions within a problem is bounded by the *opportunity structure* [4], which defines not only whether there are situations where decisions can be made, but also if designers make those decisions and whether they view those decisions as consequential to the outcomes [5]. Traditional classroom problems do not typically have this type of opportunity structure, instead relying on canonical problems with a single path towards a single right answer or, at most, allowing students to make simple choices from a limited list of acceptable ones. Because of this, students may continue to strive for the "right answer" even in situations where one doesn't exist [6]. However, successful design foregrounds the decisions that matter to the student, allowing them to direct what they learn and how they learn it. Designers make conscious decisions about what knowledge is needed to solve the problem (such as seeking out stakeholder input or determining what solutions have already been tried). They also determine their own gaps in understanding and work to fill those gaps [7]. Consequentially, successful designers take personal ownership of the problem framing process, because the framing process itself is highly personal. This ownership of the problem framing process constitutes framing agency.

What is laboratory and experimental framing agency?

In the design of experiments, students are asked to determine how requirements should be carried out to answer questions or solve problems [8]. Commonly, course-based laboratory problems are treated as well-structured, cookbook style activities in which students make few or no consequential decisions [9]. Many engineering laboratory experiments can be deterministic, and faculty focus on teaching the complexity—the number and interrelatedness of variables [1]. Such approaches typically support students to learn about the variables and their interrelations, but not the process of designing experiments. By allowing students to make consequential decisions, they may learn about both the variables and their relations, as well as the process of experimental design [10]. We argue that to learn how to direct experimental design procedures, students need experience making such decisions. Such laboratory experiments prepare engineering students for the types of ill-structured problems they will face outside the classroom as engineers [11]. Thus, developing framing agency over laboratory experiences allows students to create learning that extends outside the classroom.

What might make a simulated laboratory experiment consequential?

Simulations can allow students to gain access to experiences that, for whatever reason, are not available to them in person. However, the implementation of simulations in a laboratory includes potential concerns. Without enough support, students may disengage rather than interrogate what is happening, rendering the exercise moot [12]. The most effective simulations for learning are those that allow for students to make decisions in a guided way that also allows them to change outcomes and goals [13]. We use the construct of framing agency to evaluate the number and type of decisions that students can make within the context of simulated laboratory experiments to understand what decisions and simulation methods are consequential to students.

Methods

We used a quasi-experimental approach [14] to investigate the impacts of decision making in face-to-face and simulated experiences in chemical engineering courses that included design of experiments. We contrasted the experiences of students who completed face-to-face experiments prior to the pandemic with those who completed simulated experiments during the pandemic.

Participants & setting

We conducted the study in a research university in the American Southwest, focusing on two courses in a chemical engineering department. A total of 215 students consented to participate in the study across two years of data collection. We collected data in two iterations of two courses that made specific changes from in-person laboratory experiments to online experimentation through simulations.

The first course was a one-credit course that serves as an introduction to chemical engineering and contained primarily students in their first year of college. The first-year students worked in groups. In 2019, 71 students in 19 groups provided consent and in 2020, 51 students in 13 groups provided consent.

The second course was a three-credit laboratory course (the first of a four-course laboratory sequence) focused on thermodynamics. This course contained junior chemical engineers who worked in groups on lab activities but who completed individual assignments. In 2019, 59 students provided consent and in 2020, 34 students provided consent.

Materials and Procedures

The Fall 2019 versions of the courses included in-person laboratory experiments. Due to COVID restrictions in place during Fall 2020, we developed simulated versions of these experiments. We recount the procedures of both versions.

First year course, Fall 2019. The introduction to chemical engineering course experiment centers around designing a method to remediate water containing acid mine drainage runoff, raising the pH of the water. As part of the challenge, students are asked to do research about four compounds (limestone, activated charcoal, calcium carbonate powder, and soda ash solution at a pH of 9) and propose a remediation solution using one or more of these. In the face-to-face experiment, students measured the amount of each material they selected and put it into an empty glass column (Figure 1). Students then filtered 200mL of simulated mine drainage runoff (at a pH of 4, colored with turmeric, which convinced many students they were working with hazardous water), testing the pH of the water coming out of the column at 50mL intervals as well as timing how long it took for the entire 200mL to exit the column. Students took their data, calculated the flow rate and the amount of wastewater they could remediate per hour. They graphed their data and submitted it to a shared Google Sheet so that students could compare their results to those of their classmates. Finally, students considered how successful their design was and suggested what they would do if they had an opportunity to run the experiment again.

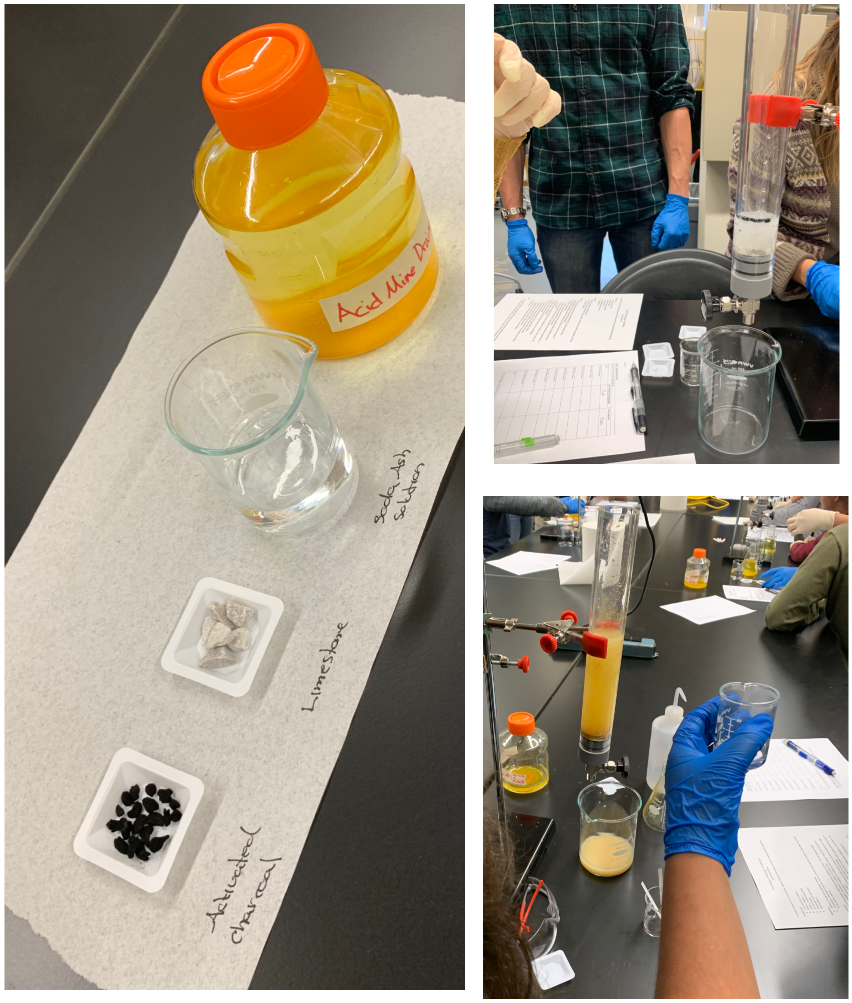


Figure 1. Materials for the acid mine drainage experiment (left); one team's column prior to adding the simulated acid mine drainage (upper right) and treatment in progress (lower right)

First year course, Fall 2020. This course contained the same problem of remediating acid mine drainage. Students did research about the same four compounds (limestone, activated charcoal, calcium carbonate powder, and soda ash solution at a pH of 9) and submitted their suggested design. Students tested their designs using an Anylogic simulation, developed via Anylogic University Software (https://cloud.anylogic.com/model/ea348854-83ba-4f23-aca6-0db78e47cfac?mode=DASHBOARD&experiment=86429e03-40d5-4eba-bca3-282cc173c186). The simulation was distributed to students through the Anylogic Public Cloud platform, which enabled easy and scalable access to the simulation through a web browser. The simulation has two modes for students to interact with. The **Animation mode** (Figure 2) provides a visualization of the experiment for students in order to help them develop intuition regarding how the chemicals mix together and how the flow rate and pH level can change in the mixture. The animation depicts a schematic view of different chemicals (acid mine drainage solution, soda ash solution, limestone, calcium carbonate and activated charcoal) being mixed together while it also provides real-time information about the pH level and flow rate of the mix, as well as the cost of the reaction column design (combination of each chemical) used as input. The animation runs for about 3 minutes while they have the option to speed up or slow down the simulation.

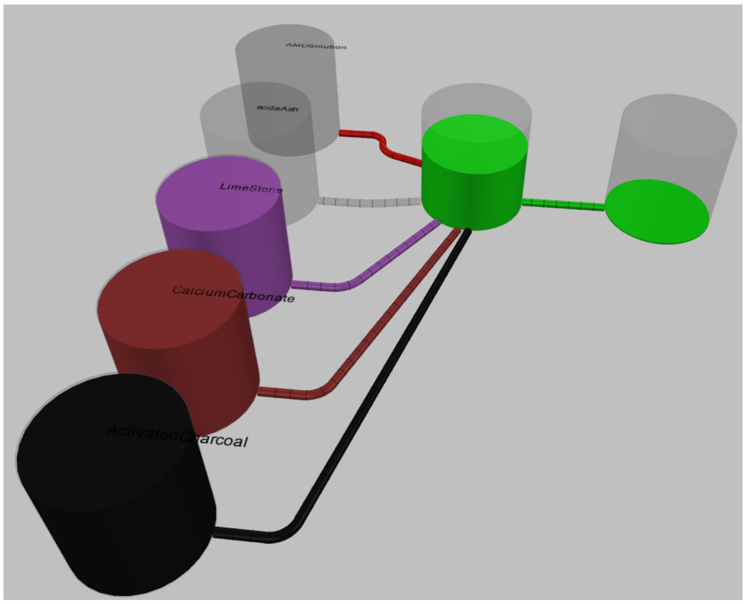
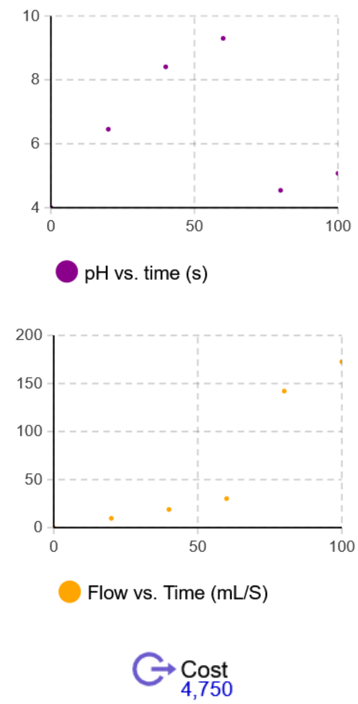
Animation snapshot	Experiment Outputs in Real-time
	

Figure 2. Animation mode of the simulation (left) and real-time outputs (right)

Students input the values they chose for each of the four compounds and recorded the pH of the acid mine drainage sample (initially at a pH of 4) and the flow rate over time as the same 200mL flowed through the simulated column. In **run mode**, the simulation instantaneously provides the corresponding outputs for any combination of input values students provide. Students are able to provide variable quantities of Soda Ash (L), Limestone (g), Calcium Carbonate (g) and Activated Charcoal (g) in their acid mine drainage treatment design and the simulation provides the corresponding cost of material and the resulting flow rate and pH change over time for that specific combination. The governing equations defining the $^{pH}/_{time}$ and flow rate were designed and implemented to mimic the actual data from the lab results from previous semesters with some added random noise to introduce a realistic uncertainty in each run. Figure 3 illustrates the user interface of the run mode for two different sets of inputs. Students then answered questions about the success and limitations of their design before being asked to revise their design to make an improvement (usually to get the drainage closer to a pH of 7, increase the flow rate, or reduce cost). They tested the revised design and determined if the revision had the intended consequence. They compared their data to the data collected in the previous year and then suggested what they would do if they had the opportunity to run the experiment again.

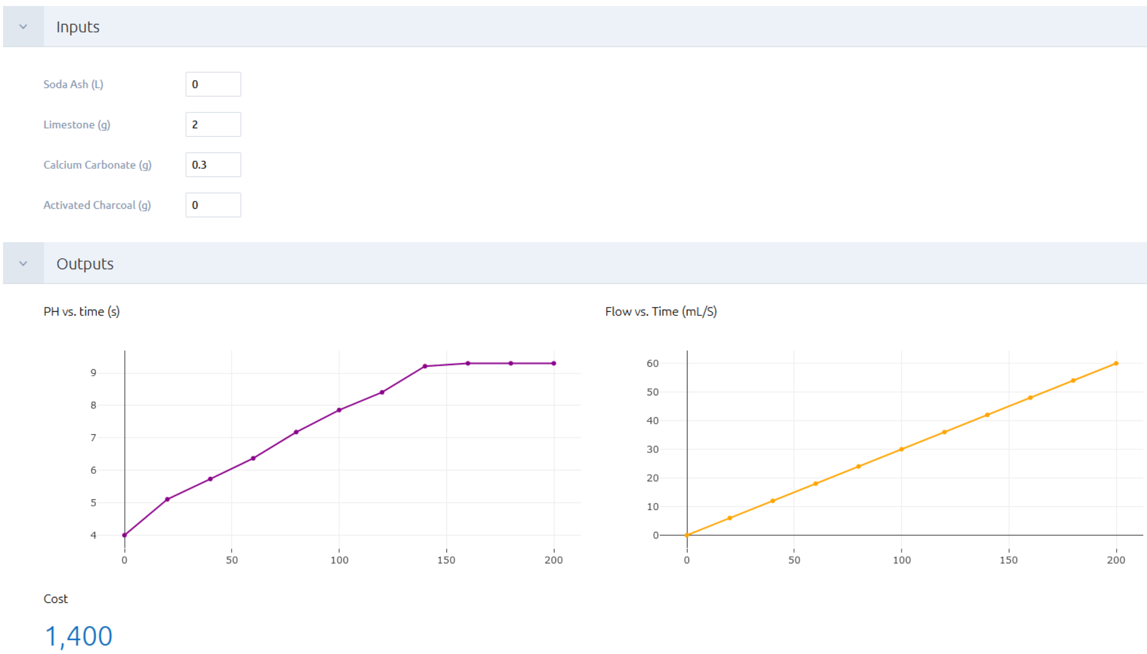


Figure 3. User interface of the run mode. Top and bottom figures illustrate two different sets of inputs and their corresponding outputs.

Junior laboratory course, Fall 2019. The junior-level course (the first in a series of four chemical engineering-specific laboratories) focuses on the thermodynamic and kinetic concepts learned in previous semesters. As part of this, students in small groups perform a bomb calorimetry experiment in which they are tasked to determine the heat capacity of the bomb calorimeter, and then use this information to determine the heat of combustion of sucrose. This experiment took place face to face, where students measured out a known mass of sample, measured the volume of water in the calorimeter, and measured a length of fuse (needed to ignite the sample). Students then ignited the sample and collected data about the temperature inside the calorimeter over time. Students collected three replicates each of the standard and the sucrose samples, then analyzed the data to calculate the heat capacity of the calorimeter and the heat of combustion of sucrose in addition to propagating the uncertainty of the measurements. Students analyzed their data and wrote short technical reports on their processes.

Junior laboratory course, Fall 2020. The instructor for the course created a simulated bomb calorimetry experiment in MATLAB (Figure 4), based in part on the data collected in previous years of the experiment. The simulation closely approximated realistic uncertainties. Students (who had prior exposure MATLAB) executed the program and selected whether they wished to run the control (benzoic acid) or sucrose. The program then output the mass of the sample, the volume of water in the calorimeter, the length of the fuse, and data for a time vs temperature graph as the sample burns. Students ran the simulation 10 times for each sample type and collated the data for analysis. Students calculated the heat capacity of the calorimeter and the heat of combustion of sucrose. They also propagated uncertainties based on their ten replicates. Students analyzed their data and wrote short technical reports on their processes.

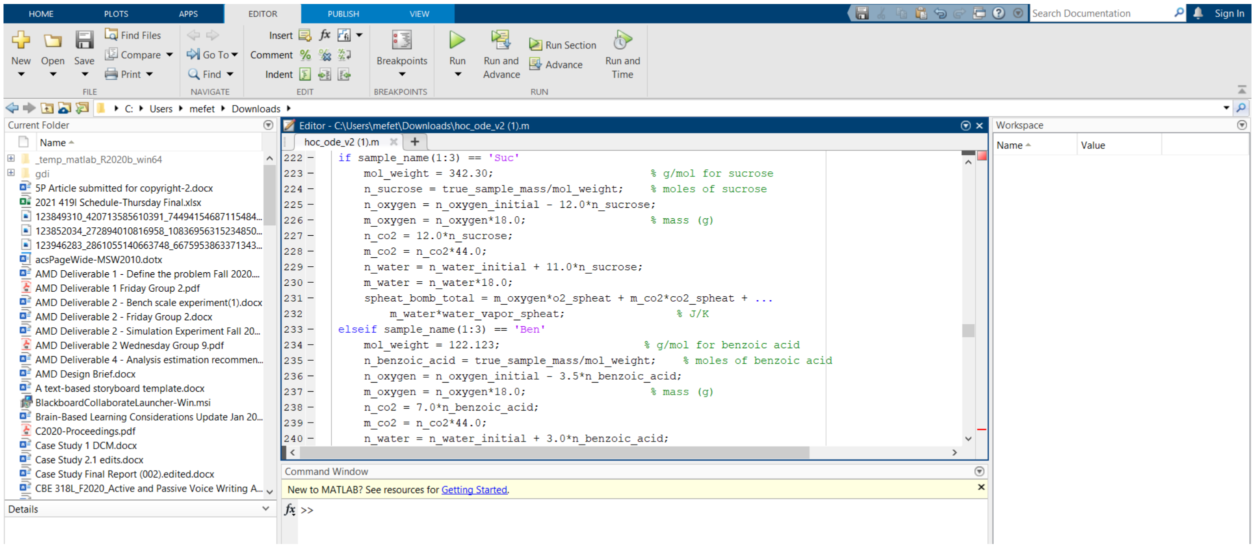


Figure 4. MATLAB version of bomb calorimetry experiment.

Data collection & analysis

The data we collected came from assignments generated during instruction. The assignment instructions did not change across the face-to-face and simulated versions, beyond making small changes to how we described the experiments. For the first year laboratory, we collected two assignments—one that asked students to propose their acid mine drainage remediation design (considering both cost and effectiveness) and another that asked students to record the data they generated (in the face-to-face or simulated experiment), conduct analysis, and propose revisions based on their results. In the junior laboratory, we collected students' analysis of their data (generated in the simulation or face-to-face experiment), the final short laboratory report they wrote about the experiment, and the reflective essays students did at the end of the semester where they were asked, in part, to think about what they learned in this lab. In both cases, we also collected field notes of interactions between students and between students and instructors during the periods where students were completing the projects.

We first analyzed the four experiments in terms of the decisions students could make, in other words, the opportunity structure presented by each experiment. Building on insights from the development of a survey to measure framing agency [15], we considered a decision as consequential if it altered the problem, the experiment, or the interpretation of results, if it could create an opportunity for learning, or if it could affect other aspects of the experiment or analysis directly.

We conducted qualitative analysis of student work. We began with an in vivo approach to ensure our assertions were grounded in the data [16]. We extended the approach reported elsewhere of identifying evidence of framing agency [17]. Such techniques build on observations that agency can be detected in talk, such as by evaluating the subjects of sentences ("I" versus "we" versus "it") and the kinds of verbs used ("did" versus "should" versus "must") [18, 19]. Extending such techniques to the analysis of written artifacts presents additional challenges, as students commonly use passive voice in technical writing, a trend that is reflected as well in publications

[20]. We therefore considered other evidence for agency and ownership, such as detailed first-hand depictions and clarity about decisions.

Results and discussion

We organize our results by research question, first detailing the consequentiality of decisions in each variant of the labs, then exploring evidence that students displayed ownership over the experimental methods, analytical methods, and their interpretation of the results.

Both the first year and junior experiments allowed students to make decisions (Table 1). In both simulation versions, students could choose to run the experiment more times than was required, a choice not available to them in the face-to-face versions. They could also choose *when* to run the experiment, a decision we deemed as not necessarily consequential. The face-to-face and simulated versions offered similar choices about experimental conditions. For instance, in both versions, first year students were constrained by budget and to four possible materials, and in both, they had access to whole-class data to use in their analysis, and though they were required to do analysis, including depicting results in a figure to back their decisions, they were otherwise relatively unconstrained. This analysis also highlights that the first year experiment, in both versions, offered greater opportunity structure. We also found evidence that students took advantage of the opportunity structure presented. For instance, in the first year simulation, we observed that students chose to run the simulation during its introduction in a synchronous lecture. A student asked, “why can’t the pH go higher than 9.3?” This demonstrates student agency when and how to run the simulation, as pushing the simulation to its limits suggests they ran it multiple times and under varied conditions.

Table 1. Opportunity structure across laboratory variants

Experiment	***Consequential decisions***	***Other decisions***
First year, face-to-face	• Which materials to use, constrained to a set of four possible materials and by budget • How to place the materials in the column • Which data, from class set, to analyze and how to analyze them	• Whether/how to document pH test strips (in addition to recording value) • How to document experimental set up (photo, diagram)
First year, simulation	• Which materials to use, constrained to a set of four possible materials and by budget • How many times to run the experiment • Which data, from class set, to analyze and how to analyze them • Which improvements to target for revision (i.e., cost, flow rate)	• When to run experiment • When to export data
Junior, face-to-face	• How precisely to measure samples • How to measure water volume and ignition wire • How to account for human experimental error	• How to record potential issues
Junior, simulation	• How many times to run the experiment	• When to run the experiment

In terms of displaying ownership, we found more differences across the two courses than across the face-to-face versus simulation variants.

In the first year course, students demonstrated that although the data they collected was simulated, the information gathered could be used and was consequential. When presenting their final designs, students made a distinction between the data they gained through simulations and laboratory data with statements such as "the simulated results of our design show…" and "we simulated how the design would work." Students recognized that the source of their data did not mitigate their ability to make decisions about their final designs. In addition, students compared directly to and evaluated their data against the data collected by their peers in the Fall 2019 course with statements such as "this makes sense compared to the data from the lab that was already collected" and "we tried a simulation that wasn't tried in the lab," connecting their information and their decision-making processes directly to real-world data.

The first-year students were able to leverage the iterative nature of the simulation to connect more deeply with implications of the experiment. After testing their initial design in the simulation, students were asked to define a point of improvement (typically something like pH change, flow rate, or price) and revise their design to improve that attribute. Here students defined their own outcomes within the experiment and evaluated if those outcomes were met.

Students in the in-person experiment were asked to suggest what they would do if they ran another experiment (including materials not available to them), but a majority of them suggested general changes to the experiment that they themselves performed such as "use more limestone and less activated charcoal". In contrast, students in the simulation version actually ran the simulations to test these ideas; when asked the same question, students who used the simulation suggested more complex and creative next experiments such as "trying cryogels because the scientific literature shows that they are extremely effective at neutralizing mercury compounds" or "using organic materials or biomaterials to change the pH as they typically are very compatible with nature." Students were able to use the information and context gathered in the simulation to think creatively and better interrogate the complex problem before them.

The first-year students in both versions demonstrated a clear understanding of how the experiment was run and the physical parameters that went into the results. In the simulation variant, we showed students how the experiment was done in person. In the face-to-face variant, most students photographed their experimental setup and added a written description of their materials. In the simulation variant, students created detailed diagrams for future experiments, indicating the process of data gathering was clear to them, even if they never set foot in the lab.

Both versions of the junior laboratory presented less opportunity structure, with most decisions focused on their analysis and interpretation of their data. In both variants, the instructor asked students to write what they actually did in the methods section of their short technical reports. Despite this, many students in the simulation variant wrote about the lab as though they had done it in person, with statements such as "we went to the lab" and "we measured out 1mg of sucrose." Some students made no mention of the simulation at all, while others mentioned it in a single sentence at the end. Those who described the simulation did not go into detail, and typically mitigated the value of simulation, "instead of going to the lab the data was collected by simulation." This is an indication that the students did not view the simulation as real, or as a method of collecting valid data.

The juniors to conceptualize the process of the experiment in their reports. Many expressed difficulty, even when given a live video of the general process, saying things like “I am still not sure if I understand how to do this experiment in the lab” and “I ended up doing a lot of outside research to figure out how a bomb calorimeter works.” This suggests that the lack of decisions in the process as well as the abstract method of collecting data separated the students from the physical process that was being simulated.

Because uncertainty was built into the simulation, students reported in their reflections a better understanding of the ubiquity of uncertainty of measurements with statements such as “I see how uncertainty is all around us” and “I didn’t understand propagation of uncertainty until I did it with this data.” In past courses, students have attributed error to human error or insufficient equipment, commenting “a better scale is needed to decrease the error” or “error comes from not putting the lid on the calorimeter.” This did not occur with the simulation, as these external factors clearly were not present, but error persisted. However, there was a learning curve as students initially (before the data analysis) assumed that there would be no error because computers don’t make errors, with many students making comments in their early drafts such as “as this is a simulation, there is no error or uncertainty.” One student commented in their reflection “I found it fascinating that you can simulate the error in a way that leads to results like in the lab.” This led to increased agency over the analysis and conclusions of the experiment, unencumbered by the errors viewed as out of their control in in-person experimentation.

When doing the analysis, students focused on the outcomes and grappled more deeply with the process. A member of the instructional team commented “I had more students come to ask for help because their answer didn’t make sense than I expected.” Rather than simply go through the motions and submit an irrational answer—something that did occur in the face-to-face variant where several students reported a heat of combustion suggesting the combustion was endothermic rather than exothermic—students wrestled with the data and sought feedback on whether it made sense or not. Several students attributed this to being able to focus on the data rather than worrying about the laboratory with comments such as “it was nice that we spent so much time on the analysis. It really helped me understand what was happening.”

Significance and implications

We found that although there are many benefits to in-person experimentation, simulations can provide students with an opportunity structure that allows them to use their agency to make consequential decisions. Attending to this opportunity structure—from the decisions students can make with the simulation through to the decisions they can make with the data they produce from their use of the simulation—can, in turn, be consequential for learning. In the simulation version of the first year course, students ran many experiments, allowing them to identify the contributions of individual materials, as well as identify the limits of combinations. In the face-to-face version, none of the students initially tested a design with a single material. Many recognized doing so would be valuable, but also likely insufficient, leaving them with many unanswered questions. For the first year students, we found that simulation contributed to learning because students made consequential decisions about the outcome of the experiment, even though they were not in the laboratory. For the juniors, this occurred when they analyzed the data they acquired from replicates, even though they viewed the simulation as artificial.

Face-to-face experiments provide critical opportunities for students to learn how to use equipment, handle samples, make critical and concrete decisions about safety, and manage moment-by-moment team interactions. Given this, we would never argue for a simulation-only approach, but instead, see great potential in using simulations in ways that are complementary to face-to-face experiments. For instance, we envision having students first conduct the bomb calorimetry lab in person, then working with the simulation, which can provide an opportunity to do enough replicates with realistic experimental uncertainties built into the simulation. This in turn will allow for more robust statistical treatment, and allows students to investigate a larger experimental space.

Across both simulations, we included uncertainty. For first year students, this contributed in part to the sense of authenticity, though it was not a focus of the course. For the juniors, it only became salient during analysis, where the uncertainties in the simulation helped teach concepts of statistics and propagation of uncertainty. Given that some students also commented in their reflections that they hadn't previously appreciated that experiments could be realistically simulated, we see a potential extension focused on giving them the MATLAB code to modify, rather than just using it as a means to run the simulation. Such extensions also allow students to explore riskier or more time-intensive or expensive experimental situations.

We certainly see value in the rich interactions that can occur in face-to-face experiments, and our results suggest future studies could investigate combinations of simulations and experiments. For instance, in future versions, we plan to study whether the simulations are more helpful as pre-lab or post-lab activities that deliberately complement and extend the face-to-face experiments by expanding the opportunity structure, providing them with greater agency to make decisions that are consequential to their experimentation and interpretation, and attendant learning.

Our study extends prior work on framing agency [17], suggesting that it is not bound only to engineering design settings, but that it can also be salient for other ill-structured problem work, including the design of experiments. In particular, the notion of consequentiality of decisions provided a fruitful framework for evaluating the aspects of both face-to-face and simulated laboratory experiences that contributed to learning. While limited in context and scope, future studies may use this framework to better characterize the learning potential from expository, inquiry, discovery, and problem-based laboratory instruction [10].

We acknowledge a few limitations of our study that can be addressed in future work. First, we lacked control groups, and all students were enrolled in the same engineering department. We invite comparison studies in other disciplines to expand on our findings, especially with a focus on framing agency, as this may vary somewhat by discipline. Second, we used two simulation platforms, Anylogic and MATLAB, simply because we had access and knowledge needed to use them. There are many options for building, adapting, or using simulations:

- Netlogo https://ccl.northwestern.edu/netlogo/
- Anylogic cloud https://cloud.anylogic.com/models
- Phet https://phet.colorado.edu/
- LearnChemE http://www.learncheme.com/
- Math Works (MatLab) https://www.mathworks.com/discovery/simulation-software.html

Few simulation systems include tracking, in part because running and tracking can be demanding in terms of processing power, making them unsuitable for regular classroom use. The consequence of this is that we were not able to document the number of iterations students ran. While many students reported running the acid mine simulation many times, in part to determine if they could “break” it, we do not know how many students ran it more than the required two times. In future, one way we plan to address this is to ask students to take screenshots of at least three to five versions of their inputs and outputs.

For more information as well as resources about designing consequential simulations, self-enroll in the mini canvas course here about integrating simulations with face-to-face experiments https://canvas.instructure.com/enroll/6DF8JL.

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