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Learning to Design: Authenticity, Negotiation, and Innovation*

VANESSA SVIHLA[1], ANTHONY J. PETROSINO[2] and KENNETH R. DILLER[3]
[1] The University of New Mexico, Albuquerque NM 87131, USA. E-mail: vsvihla@unm.edu
[2] The University of Texas at Austin, 1 University Station D5700, Austin, TX 78712, USA. E-mail: ajpetrosino@mail.utexas.edu
[3] The University of Texas at Austin, 1 University Station D5700, Austin, TX 78712, USA. E-mail: kdiller@mail.utexas.edu

Engineering design is a collaborative and complex process, and our understanding of how to support student teams in learning to design remains limited. By considering in-situ student design teams in a capstone biomedical engineering course, we are afforded the opportunity to contrast two versions of a non-sponsored project, then consider expert perceptions of their later sponsored designs. Data from two cohorts of the course yield compelling contrasts for authentic design learning experiences. We found that a non-sponsored redesign project led students to values customer needs and to use them to define the design problem, whereas in a kit-based version this did not occur. We also found that greater perceived opportunities to negotiate one's understanding within a team predicted more innovative team designs.

Keywords: engineering design; innovation; expertise

1. Introduction

In Educating the Engineer of 2020, a report for the National Academy of Engineering, the needed attributes of engineers of the near future are entailed as follows: engineers need to possess strong analytic skills, practical ingenuity, creativity, communication, business and management skills, professionalism, leadership, high ethical standards, and be lifelong learners [1]. Furthermore, they will need 'something that cannot be described in a single word. It involves dynamism, agility, resilience, and flexibility' (p. 56). We view design activity to be a context in which many of these characteristics are particularly needed, and thus see design activity as integral to engineering education. We present data and analysis from two cohorts of a university capstone biomedical engineering design course.

We conducted our research with student teams learning to design. We investigate design skills, predicting that students' learning of designerly aspects of problem solving, (e.g., incorporating customer needs), will depend upon the need to practice such skills. We hypothesize that learning to design involves acquiring and applying factual and conceptual knowledge but that doing so is not sufficient to predict innovative design. Finally, we consider why team design in particular offers potential for learning, predicting that when students perceive opportunities to collaborate and share their ideas that they will tend to produce more innovative designs.

We next frame this study by considering research on the development of expertise in general and in design specifically, also considering aspects of collaboration as they relate to problem solving and developing expertise.

Studies of engineering design have focused primarily on contrasting novice with intermediate or expert designers or on categorizing design skills of experts. In most cases, these studies have occurred in isolation of other people, (though resources have been available during tasks), and the design tasks have been of limited duration (generally under two hours) [2]. For instance, individual professional engineers spent two hours designing an attachment for placing a certain bag onto a certain bike frame [3]. Dorst [4] raised the issue of using such experimental tasks for the study of design. Although these tasks seem to warrant the generation of a taxonomy of design problems, it is difficult to know if the tasks that have been the focus of study are representative, especially as most have occurred in laboratory settings, not in design studio settings. Therefore, the review of research on design must be considered somewhat tentative in its bearing on extended team design *learning*.

Though there are some who consider design to be more art than method [5], many researchers have found it fruitful to operationalize design process as a type of problem solving. Jonassen [6] categorized problems by providing the dimensions of structure, complexity, and domain specificity. Well-structured problems involve the application of finite concepts and rules in a predictive and prescriptive manner, such that the solutions are predictable. Ill-structured problems *emerge* in life and require the integration of various domains of knowledge and skills. Ill-structured problems involve incorporating preference or opinion while making judgments about unknown and uncertain elements, such that there

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are multiple solution paths to multiple, unpredictable solutions. Based on such a categorization, design problems would be considered ill-structured.

Complexity is a function of the number of variables, the amount of interconnectedness between variables, the type of relationships between variables, and the stability of all of these parameters over time [6]. Dynamic problems are more complex than static problems. Domain specificity refers to the degree to which domain-specific versus domain-general methods may be employed in solving a problem. Domain-specific problems are situated and contextualized. Utilizing such a categorization, design problems would be considered complex and domain specific.

Additionally, design problems are said to co-evolve with their solutions [7]. As an illustration, consider a situation in which the same design problem is assigned to 50 teams; according to Harfield [8], this would result, not in 50 solutions to the same problem but 50 solutions to 50 different problems. The problem to be solved, and the resultant solution, will depend on many issues, including context, bias, prior experiences, and prior knowledge [8]. Because of their ill-structure, the incorporation of judgment and style, and the co-evolution of problem and solution, design problems have been labeled 'wicked' [9]. This discussion of design is general enough to apply to many types of design; next we discuss engineering design in particular.

Problem Scoping: Good design is considered to be tied to good problem scoping [10], which involves clarifying and defining the problem as well as gathering information. Design is systematic, and designers start from first principles [11], or fundamental physical principles [12]. Expert designers, more so than novices, may question the data that they are given in a design task [13, 14]. Experts tend to take a broad approach informed by personal preference and then explore the problem space in a principled manner [15], relying on procedural strategies. In contrast, novice designers rely on declarative knowledge and a depth-first approach [16]. Expert designers gather more data than novice designers [10]. Perhaps more critical, experienced designers pay better attention to the customer needs, logistics, and constraints in the design task [17]. Novices tend to spend more time on problem scoping than experts, but to less beneficial effect [10].

Becoming Solution Focused: The design problem and solution co-evolve, and multiple possible solutions exist [8]. As designers become solution focused, they populate the design process with dynamic, temporary goals. Strategies for solving problems may be local or global, as ill-structured problems are decomposed into well-structured subproblems [15]. This requires frequent cognitive switching, but does not necessarily involve consideration of broad alternatives [18]. Experts employ flexible strategies [10], as opposed to the trial-and-error strategies commonly used by novices, and this offers clear advantages to expert designers, who evaluate prior to making a decision [13]. Designers must consider alternative solutions [10], and they commonly accomplish this via analogy. Experienced designers have a large repertoire of many more relevant analogies based in previous design experience than novices [19]. Experts in design rely heavily on ideation techniques, which foster analogical reasoning [20], and on prior relevant experiences [8, 13].

Research has shown that myriad experiences are needed to fully apprehend a concept or skill [21, 22] and that understanding may be revised with addition of new cases relevant to a skill or concept [23]. With experience, designers become more aware of issues related to the task at hand and efficiently can judge which are most problematic. They also become aware of the reasons for use and processing behind a device. This makes expert designers more attuned to trade-offs and limitations and provides them with the ability to question whether a design is worth pursuing, to keep their design options open, or even to reframe the problem into a new design task [13]. Whereas experts may rely on their past design experiences as they proceed in a design, novices might draw upon prior coursework experiences, which in the context of learning to design through project based learning [24] may or may not be relevant. We have examined the aspects of design that we believe lend themselves to a focus on the individual and the cognitive processes involved with design as a problem solving activity.

2. Participants and methods

The participants of this study were senior bioengineering students enrolled in the capstone, year-long design class at The University of Texas at Austin. Like many capstone models, this course is taken by senior students after completion of a course of study including many science, mathematics, and engineering science courses [25]. The study gained IRB approval and students included in the study gave consent. Cohort one comprised students from fall 2005 through spring 2006 and cohort two comprised students from fall 2006 through spring 2007. Design teams were organized by the course instructors and consisted of three or four students. The instructors made sure that non-native English speakers were distributed across design teams such that no team consisted entirely of non-native English speakers.

The class was taught in two consecutive semesters by two different professors. The class met intermittently, with lectures targeting specific topics and related assignments. The four teaching assistants (who varied from semester to semester) played a large role in facilitating the students' learning; the teaching assistants had approximately 100 contact hours with the teams and helped with assessment of students' work. The teaching assistants met weekly with the instructors to discuss upcoming assignments, team progress, and to surface any issues teams might be having. Additionally, teams were mentored by faculty advisors and their sponsors, though these interactions varied across teams.

Both cohorts completed a preliminary project prior to beginning their sponsored project (Figure 1). Cohort one completed a kit-based mini-project, in which all teams designed digital stethoscopes with the constraint that they functionally incorporate a specific material. Cohort two completed a redesign project, in which teams selected biomedical devices, such as nicotine patches, inhalers, and pregnancy tests, and redesigned some aspect of the device based on customer needs.

After completion of the preliminary project, the teams were selected by sponsors to design a biomedical device or protocol (Appendix A). The projects came from hospitals, industry, government, and universities, and while they varied in terms of difficulty, all were real-world, complex, and ill-structured. Additionally, all projects required skills and content knowledge that were not part of the degree program. For example, projects involving circuits may have been challenging because these students did not have extensive experience with circuits, whereas the same project may have been comparatively straightforward for an electrical engineering student. Students were given instruction during lectures and completed activities relevant to their designs and the nature of engineering design. Activities included a number of tools common to both engineering design education and to professional design. They used Gantt Charts to keep track of deadlines and were allowed to select from a variety of commonly used ideation techniques (e.g., brainstorming) to support them in coming up with possible design solutions. Voice of the Customer interviews combined with Pugh Charts served to help them identify and prioritize customer needs, which were then placed in a House of Quality which allowed them to compare existing and possible designs to decide how to proceed. These tools reinforced the idea that the design should flow from customer needs, a challenging concept for students to understand. Additionally, students submitted progress reports to keep their sponsor apprised of their progress, and made several oral presentations to their teaching assistants and course professor; these and their design journals helped the teaching assistants and professor keep tabs on their progress.

Fall Semester				Spring Semester	
Cohort 1 N=86	Pre-test	Mini-project	Mid-test	Sponsored project	Post-test
Cohort 2 N=82		Redesign project		Sponsored project	

Fig. 1. Course format and comparison of preliminary projects.

This study reports a sequence of analyses of in-situ student team design learning: First, we compared the two versions of a preliminary design activity and considered the dimensions by which they differed; then, we examined the conceptual knowledge and innovativeness of team design work as part of an industry-sponsored design project; finally, we considered variables that might explain innovation in student design work. In doing so, we addressed the following research questions:

- How might a brief, non-sponsored design project be used to introduce engineering design following a sequence of engineering science coursework?
- What dimensions might increase the authenticity of such a project?
- How might the preliminary design project impact the quality of conceptual understanding and innovation in the sponsored design work?
- How do students' perceptions of opportunities to negotiate their own learning relate to the quality of conceptual understanding and innovation in the sponsored design work?

We investigated design skills, predicting that students' learning of *designerly* aspects of problem solving, (e.g., incorporating customer needs), would depend upon the need to practice such skills. We hypothesized that learning to design involves acquiring and applying factual and conceptual knowledge but that doing so is not sufficient to predict innovative design. Finally, we considered why team design in particular offers potential for learning, predicting that when students perceive opportunities to collaborate and share their ideas that they would tend to produce more innovative designs.

3. Measures and results

3.1 How might a brief, non-sponsored design project be used to introduce engineering design following a sequence of engineering science coursework?

Our first research question investigated two iterations of a two-month long non-sponsored design project intended to introduce students who had completed the engineering science sequence to engineering design. Cohort one completed a *kit-based design project* and cohort two completed a *redesign project.* We developed an assessment and coding rubric to measure students' conceptual design skills.

An authentic design task, created by one of the authors (KD) was used to capture some of the changes in how students embark on design process. This particular design problem (Appendix B) was considered by experts to be extremely challenging, with one expert skeptical about whether it could actually be designed (though it has since been designed for use in the US military). The task was developed by an internationally recognized authority on the application of the principles of heat and mass transfer and thermodynamics to the solution of various types of biomedical problems. This design task was used to examine changes resulting from experience in design, and involved designing a device for treating hypothermia in war conditions. The problem included strict constraints as the device must be useable in battle conditions and be able to withstand being dropped from a helicopter without a parachute. Students were told they will not be able to proceed very far into the design, but rather were asked to demonstrate how they would *begin* to design the device. This same task was posed to students at three time points across the design course: as a pre-test, given during the first week of class; as a mid-test, given after completion of a preliminary project; and as a post test, given at the end of the sponsored project. Students completed this task individually.

In order to capture the changes over time on this measure, a coding scheme was developed. This coding scheme was initially based on expert performance on the measure then modified based on discussions with domain experts and learning scientists. The coding scheme (Table 1) included categories about the *feasibility* of the design, such as the cost of materials and federal regulations; the *voice of the customer*, including the needs of the various customers the device would be used on and by; and the *diagram*, including the direction of blood flow, a heat exchanger, and the heart as the pump. The student work was binomially coded with present/absent for each of the subcategories. Reliability of coding was established by having another learning scientist code twenty percent of the tests, resulting in a satisfactory 90% agreement. Though most categories showed increases over time, few showed significant differences over time or across cohorts.

Both cohorts oriented to more of a design focus by the post test, meaning that their designs included more information about construction, increased use of and higher quality schematic views, and more attention to the *voice of the customer*. A typical response on the pretest, for example, addressed the scientific aspects related to the heat-transfer inherent in the problem. A typical response from the post test was more likely to address concrete issues of design, including insulation, temperature monitoring, or how blood could be warmed without damage. Note that although the changes, on average, appeared to be small in absolute terms, this coding scheme was intended to capture novice through expert performance, meaning that in this relatively brief time interval (less than one year), we would not anticipate that students would move

Table 1. Coding scheme developed to capture changes in student conceptual design

Feasibility	
Category	**Examples of student work**
Price	It can't be too expensive
Regulations	It must meet FDA requirements
Materials—durability and/or biocompatibility	Use tubing that is lined with something to prevent blood clotting
Voice of the Customer	
Category	**Examples of student work**
Addresses patients' needs	It has to be able to be used while laying down
Addresses medics' needs	A display panel shows blood temp going in and out
Addresses needs of the demanding setting	The butane must be contained effectively so it won't explode when dropped 150 feet
Diagram	
Category	**Examples of student work**
Material	Shows accurate blood flow direction
Heat	Shows heat source and method
Mechanical	Shows heart as source for pressure
System Boundaries	Shows person, tubing, and the device

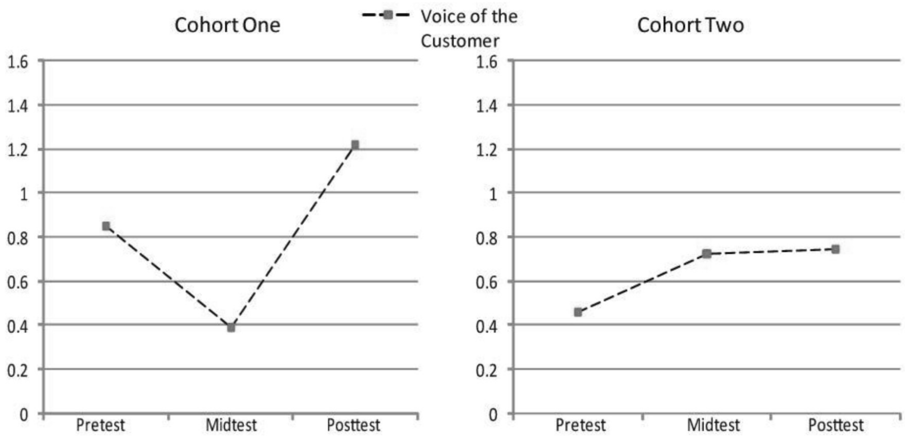

Fig. 2. Test averages for Cohorts one and two for voice of the customer.

from novice to expert. Given this limited increase, statistical analysis was critical for detecting significant changes.

At the time of the pre-test, there were no significant differences between cohorts. When examining the trajectories over time and by cohort, a troubling decrease in *voice of the customer* could be seen for cohort one at the mid-test, whereas for cohort two there was an increase (Fig. 2). This contrast occurred at the end of the preliminary project, and could indicate that the two different projects (kit project and redesign project) resulted in different learning experiences for the two cohorts. Though this contrast is visually striking, because of the restricted range of the scores it was critical to also apply statistical analysis in order to infer if these trends were significantly different.

Most statistical analyses assume that students' scores are independent of one another. While this may be a reasonable assumption at the time of the pre-test, it is no longer a reasonable assumption by the mid-test, even though they completed the tests individually; this is because an individual's learning will have been impacted by the experiences within the team. We view individual student learning in design to be greatly impacted by the team experiences, and consider the design team to be a critical unit of analysis. In order to take these aggregate factors into account, we employed Hierarchical Linear Modeling (HLM) to analyze these data [26]. HLM is an extension of ordinary least squares (OLS) regression analysis that accounts for correlations between students. OLS regression, by contrast, would produce insufficient standard errors. HLM allows sources of variance to be partitioned by level (student, team) and to interact across levels (Equations 1–3). In order to contrast the cohorts, we applied a two-level model focusing on the relationship between the pre and mid test across cohorts, excluding the post-test because there was no significant difference between cohorts at this time point.

This method allowed us to explore how variance in mid-test scores on *voice of the customer* was partitioned based on the apparently different relationships across the cohorts (Fig. 3). In order to accomplish this, we included explanatory variables as follows (Table 2): level one included the pretest scores relating to *voice of the customer* (VOCPre) as an explanatory variable, and the mid-test *voice of the customer* scores (VOCMid) as the outcome variable (Equation 1). Level two identified students in teams, treating cohort as an explanatory variable in the model (Equations 2 and 3).

Level 1 Model: Students

(1) $\mathrm{VOCMid}_{ij} = \beta_{0j} + \beta_{1j}{}^*(\mathrm{VOCPre}) + r_{ij}$

Level 2 Model: Teams

(2) $\beta_{0j} = \gamma_{00}{}^*(\mathrm{Cohort}) + u_{0j}$

(3) $\beta_{1j} = \gamma_{10}{}^*(\mathrm{Cohort}) + u_{1j}$

The parameters for this model, which included cohort both as a main effect and as an interaction term with pretest, may be interpreted as follows (Table 3): Students in cohort two scored 0.303 points higher on the mid test than students in cohort one (Equations 4 and 5). This difference is statistically significant, $t = 2.155$, $p < 0.05$. Average pre-test scores predicted mid test scores 0.027 points higher, but this is not significantly different from zero.

(4) Cohort one: VOCMid = 0.414 + 0.27(VOCPre)

(5) Cohort two: VOCMid = 0.716 + 0.405(VOCPre)

Table 2. Variables in the model of midtest scores on voice of the customer

$VOCMid_{ij}$	outcome variable; score on design mid-test for *voice of the customer* for student i in team j
β_{0j}	average pretest score for team j
β_{1j}	average relationship between pre and mid test scores for team j
γ_{00}	average score for cohort one
γ_{10}	difference between cohort one and two
r_{ij}	Difference between a student's score and the team average
u_{0j}	Difference between a team score and the average team score

By including team and cohort information in the model, the variance remaining in mid-test VOC scores was 0.041. The statistical test result suggested that this remaining variance was not significant, $\chi^2 = 36.718$, $p > 0.05$. The intraclass correlation, derived by comparing the amounts of variance partitioned into student and team levels provided an estimate of clustering. In this case, the intraclass correlation was 9%, indicating that approximately 9% of the variance in scores of mid-test VOC was due to teams. This would have been missed in OLS regression.

The results of this type of statistical modeling are complex but offer significant advantages over OLS regression when a student's learning is expected to be influenced by his or her team mates. By using this type of modeling, we found that cohort two achieved significantly over cohort one, and that individual student's scores were impacted by their team mates. Similar analyses were explored with other coded categories from the *design skills* test, but no significant differences were found. This includes the pre-test, for which there were no statistically significant differences across cohorts, adding strength to the idea that differences found on VOC may reasonably be attributed to the experiences of the students during their preliminary projects.

We next explain this finding by considering the types of activities students engaged in for each project, and how this might inform the development of design activities for students, even given a limited budget.

3.2 What dimensions might increase the authenticity of a non-sponsored design project?

The redesign project reflected authentic engineering design practice better than the kit-based project in consequential ways. In the redesign project, teams chose a device to redesign and then relied upon customer needs in order to decide upon a design path. This meant that they had to define their design problem and determine which solution would optimally meet the needs and constraints of their project. This is in contrast to the teams who designed stethoscopes from a kit of materials, who felt that the customer was irrelevant to their process and saw the project as arbitrary. This is evidenced by the change in perception of the *voice of the customer* activity by cohort one students. Following the kit-based design activity, cohort one students rated the *voice of the customer* activity as not very useful to neutral ($M = 2.89$, $SD = 1.25$, on a five point scale). At the end of the sponsored design project, cohort one students reported the *voice of the customer* activity as neutral to somewhat useful ($M = 3.66$, $SD = 1.30$, on a five point scale), and this change is significant, $t(150) = 3.69$, $p < 0.01$. In contrast, at both points, cohort two students report the activity as somewhat useful to useful for both the redesign ($M = 4.53$, $SD = 0.74$) and the sponsored project ($M = 4.69$, $SD = 0.60$).

By including an authentic reason for teams to base their design upon customer needs, the students had opportunities to pose relevant design questions. In the kit-based project, the constraints were artificial, especially given that the kit contained extraneous materials, which, in absence of the artificial constraint, could have been used to create a simpler, yet more effective design. These findings suggest that teams in cohort two had significantly different learning experiences during the preliminary project than cohort one. Keeping in mind that cohort one teams all designed stethoscopes whereas cohort two teams selected biomedical devices to redesign, we expected there to be differences in their performance. The students engaged in the less structured redesign task achieved significantly higher gains in

Table 3. Conditional Hierarchical Linear Model of voice of the customer

Fixed Effect	**Coefficient**	**SE**	***t* ratio**	***p* value**
Intercept, γ_{00}	0.414	0.098	4.242	0.000
Cohort effect, γ_{01}	0.302	0.140	2.155	0.037
Pre-test effect, γ_{10}	0.027	0.142	0.187	0.853
Cohort effect on Pre-test, γ_{11}	0.135	0.209	0.648	0.520
Random Effect	**Variance Component**	**df**	χ^2	***p* value**
Team level, u_{0j}	0.041	27	36.718	0.100
Slope, u_{1j}	0.036	27	29.594	0.332
Student level, r_{ij}	0.433			

scores on *voice of the customer* over the students in the more structured kit-based design task. By allowing students to select devices, and to determine, based on actual customer interviews and needs, what direction the redesign should take, students learned to value the *voice of the customer*. This happens naturally in the more authentic sponsored projects, but did not happen in the confines of the more sequestered kit-based design task. Although students went through the same basic steps, they did not have a need to incorporate the *voice of the customer*. It Additionally, based on course instructor surveys, student reviews of the two projects also differed, with students much more satisfied with the redesign project [27, Personal Communication].

3.3 How might the preliminary design project impact the quality of conceptual understanding and innovation in the sponsored design work?

Next, we report on expert evaluation of the industry-sponsored team design work from two time points to understand whether the preliminary design project might have impacted the quality of conceptual understanding and innovation of the sponsored design projects. We presented domain experts with team design work from two time points and asked them to rate the design work according to two dimensions: innovation and conceptual understanding. Three of the domain experts had familiarity with the dimensions from prior affiliation with our research. The other domain expert had limited familiarity with the dimensions; thus, we provided definitions as follows: c*onceptual understanding* is the ability to accurately and appropriately apply factual and conceptual knowledge in design work; and *innovation* is the ability to find a novel way to address the design problem. The experts provided scores ranging from one to five on each dimension, with five representing the highest levels of innovation or conceptual understanding. This method has been used effectively elsewhere [28] and is employed because it allows the experts to leverage their own expertise in developing levels [29]. Note that this method does not involve a rubric or coding, but relies on the experts to use their judgment [24]. This method takes advantage of the complex reasoning that even an expert may struggle to explain, but depends on establishing reliability in order to be considered robust; how we accomplished this will be described after detailing the process.

Scoring, rather than ranking, was preferred because the design projects differed greatly, making it difficult to compare some projects. Additionally, ranking may not have captured how different two projects were as the scale is not necessarily interval, such that the difference between teams may be inconsistent. The design project definitions, completed at the end of the first semester, and the final project designs were scored according to the dimensions of innovation and conceptual understanding. Scoring all teams into levels (one to five) was a brief task (~hour) completed individually. The scorers took the task seriously, though they all expressed concern because it seemed to them that what they were doing was not 'scientific' or something that they could put into words. Despite their concerns, their scores were remarkably similar, indicating that this technique captures expert judgment that would otherwise be very difficult to capture.

The primary scorer was the course instructor, who, in addition to being a domain expert, has collaborated for eight years with learning scientists and other domain experts involved in developing research on these constructs [30, 31]. His position as course instructor and as a researcher with our group gives him a unique perspective on understanding and evaluating the students. While we established reliability with other experts, the mean scores for their scores would not provide the fidelity of the instructor's scores because the other experts could not incorporate a full picture of the gains many teams made. Because this is a study of students, not of experts, and because students cannot be expected to reach expert levels in one course, only one who is aware of the students' prior knowledge and experience can deeply assess what was novel for them. Greater expertise leads to more complex, deeper categories [29]. A score by someone without this depth of understanding would not capture subtle differences that speak to greater or lesser gains during the design process [24].

However, we recognized the need to establish the reliability of the scores from the course instructor. To this end, we asked the course instructor to provide scores a second time, approximately two months after the course ended. While not identical, the scores were reliable (91% of his rankings on innovation and 96% on conceptual understanding). We also had the executive summaries of the final designs and project definitions scored by three additional experts. These scorers did not have the opportunity to discuss their scoring with each other; thus, their scores may be considered independent of one another. Three teams' scores were omitted because these teams provided inadequate executive summaries, such that the experts had insufficient information for scoring these teams. In accordance with common practice, we report a consensus estimate of percentage agreement reliability. Because our scale included greater than four possible outcomes (meaning that the experts scored the design work from one to five), we include adjacent categories in determining agreement [32]. One expert was a biomedical engineering faculty member at the same institution as the instructor and has taught the first half of the design course. Her scores were very similar to the primary scorer (84% on innovation and 96% on conceptual understanding). She had greater familiarity with the teams than the other two experts, who taught biomedical engineering at a private university. These two experts had a high degree of similarity with each other (95% on innovation, 91% on conceptual understanding) but a somewhat lower similarity with the instructor (79% on conceptual understanding and 90% on innovation). In a discussion of the causes for this, these experts volunteered two possibilities: first, the executive summaries provided a less complete understanding of the projects, and second, the design projects at their university tend to be less constrained that the design projects in this study.

The course instructor's scores were examined for correlations. For cohort one (Table 4), final design scores on conceptual understanding correlated strongly and positively with final design scores on innovation, $r = 0.834$. This finding suggests that both aspects are part of expert design and can be learned together. Although not quite significant, higher project definition scores on innovation correlated to higher final design scores on conceptual understanding, whereas there was no significant relationship between project definition scores on conceptual understanding and either final design scores.

For cohort two (Table 5), project definition scores on innovation correlated positively to final design scores on innovation, $r = 0.665$, and project definition scores on conceptual understanding correlated positively to final design scores on conceptual understanding, $r = 0.546$. As with cohort one, there was no relationship between project definition scores on conceptual understanding and final design scores on innovation. For both cohorts early conceptual understanding did not correlate to final design innovation.

This finding is compelling because it runs counter to how we generally teach: develop conceptual understanding and skills before having opportunities to apply them. In a retrospective of Bloom's Taxonomy, Anderson, Sosniak and Bloom [33] clarify the original intent and describe some of the unintended consequences of the Taxonomy: the Taxonomy has been narrowly applied, and interpreted as a listing of cumulative skills which must be learned in order. This has led to a situation in which students are expected to master factual knowledge before conceptual knowledge, and both before engaging in higher order thinking skills. Much of instructional time is taken up with knowledge and rote learning, whereas a mere fraction is spent on 'higher mental processes that would enable students to apply their knowledge creatively,' yet 'we find ourselves in a rapidly changing and unpredictable culture' in which 'much emphasis must be placed on the development of generalized ways of attacking problems.' The lower level skills can be learned when higher order activities are the focus [33].

w>A multiple regression found a significant difference in innovation and conceptual understanding scores across cohorts, $F\ (4, 40) = 3.173$, $p < 0.05$. Post hocs revealed no significant differences on project definition scores of innovation, final design scores on innovation, or final design scores on conceptual understanding, but did find a significant difference across cohorts on project definition score on conceptual understanding, $t = 2.750$, $p < 0.01$, with cohort two teams rated significantly higher than cohort one teams. This difference across cohorts may be interpreted in several ways: one explanation could place variance in the students. However, on many demographic measures, they are identical; there is no significant difference across cohorts on the pre-test, SAT scores, high school GPA, college GPA, parent's education, or ethnicity. Both cohorts completed the same prior coursework, and similar numbers of students completed summer internships. Though we cannot completely discount individual differences, these similarities, particularly those that relate to factual and conceptual knowledge tend to suggest that this is not the critical

Table 4. Correlations among scores on design work, cohort one

		Project definition scores		**Final design scores**	
		Conceptual understanding	**Innovation**	**Conceptual understanding**	**Innovation**
Project definition scores	**Conceptual understanding**	–	0.267	–0.028	–0.030
	Innovation		–	0.397	0.141
Final design scores	**Conceptual understanding**			–	0.834*
	Innovation				–

* Correlation is significant at the 0.01 level (2-tailed); n = 22.

Table 5. Correlations among scores on design work, cohort two

		Project definition scores		Final design scores	
		Conceptual understanding	**Innovation**	**Conceptual understanding**	**Innovation**
Project definition scores	**Conceptual understanding**	–	0.150	0.546*	–0.003
	Innovation		–	0.154	0.665**
Final design scores	**Conceptual understanding**			–	0.126
	Innovation				–

* Correlation is significant at the 0.01 level (2-tailed); n = 22.

difference, given that the significantly different score was also for factual and conceptual knowledge and further did not persist beyond the sponsored project experience. Another explanation could be that there are diverse ways of proceeding in design, particularly in novice design, resulting in greater variation than would be expected among experts. However, there is no reason to assume that one cohort would have greater variance than the other, or that it would be revealed only on the project definition scores and only for conceptual understanding. Another explanation is supported by findings from the pre and mid design tests. The cohorts had significantly different learning experiences during the preliminary projects, and therefore began their sponsored projects with different preparation. It is not surprising that measures taken two months after the mid-test would reveal a difference between cohorts, but it is reassuring that later measures do not, meaning that the sponsored projects provided authentic motivating learning experiences.

This is further supported by team level OLS regression relating aggregate team scores from the pre and mid tests to the final expert scores for innovation and conceptual understanding (Tables 6-9). Variance in the final expert scores could not be explained by pre-test scores. This was true for both conceptual understanding (Table 6) and innovation (Table 7), and in both cases produced a model that did not satisfactorily explain variance. Further, this established that initial scores this test of design skills held little predictive value for recognizing a student's potential as a designer.

However, by relating the final expert scores to the team aggregate mid-test scores using regression, we found that while it was possible to account for significant variance in team scores of final conceptual understanding (Table 8) using scores from the mid-test, $F(41, 3) = 3.989$, $p < 0.05$, accounting for final innovation (Table 9) scores was more challenging. Higher expert conceptual understanding scores on final designs were predicted by higher scores on the mid-test on *team feasibility* and *team voice of the customer*. This relationship is compelling because it showed a connection between skills learned in the preliminary project and the final design project,

Table 6. Linear model of expert conceptual understanding scores of team final design work

	Unstandardized coefficients		Standardized coefficients		
	B	**Std. error**	β	***t* ratio**	***p* value**
Constant	2.176	0.435		4.999	0.00
Pre-test team feasibility	0.561	0.438	0.206	1.280	0.21
Pre-test team VOC	0.264	0.342	0.123	0.771	0.44
Pre-test team diagram	0.086	0.249	0.053	0.345	0.73

Dependent variable: final conceptual understanding $r^2 = 0.071$.

Table 7. Linear model of expert innovation scores of team final design work

	Unstandardized coefficients		Standardized coefficients		
	B	**Std. error**	β	***t* ratio**	***p* value**
Constant	2.789	0.476		5.864	0.00
Pre-test team feasibility	0.521	0.479	0.174	1.087	0.28
Pre-test team VOC	0.378	0.374	0.161	1.011	0.32
Pre-test team diagram	–0.077	0.272	–0.043	–0.283	0.78

Dependent variable: final innovation $r^2 = 0.081$.

Table 8. Linear model of expert conceptual understanding scores of team final design work

	Unstandardized coefficients		Standardized coefficients		
	B	**Std. error**	β	***t* ratio**	***p* value**
Constant	1.836	0.352		5.213	0.00
Mid-test Team Feasibility	1.428	0.546	0.450	2.617	0.01
Mid-test Team VOC	0.357	0.174	0.298	2.058	0.05
Mid-test Team Diagram	–0.171	0.367	–0.078	–0.465	0.64

Dependent Variable: final conceptual understanding $r^2 = 0.200$.

Table 9. Linear model of expert innovation scores of team final design work

	Unstandardized coefficients		Standardized coefficients		
	B	**Std. error**	β	***t* ratio**	***p* value**
Constant	2.862	0.411		6.967	0.00
Mid-test Team Feasibility	0.487	0.637	0.140	0.765	0.45
Mid-test Team VOC	0.509	0.429	0.211	1.187	0.24
Mid-test Team Diagram	–0.037	0.202	–0.028	–0.182	0.86

Dependent Variable: final innovation $r^2 = 0.099$

suggesting that early and less involved projects that provoke authentic design activities—such as considering design feasibility and customer needs—may lead to different learning in later, more authentic design experiences. This has implications for how design experiences might be taught.

We have established that the more authentic design experiences lead to designs that were perceived by experts as including expected conceptual understanding. We have shown a relationship between skills learned during a preliminary project and later expert scores of conceptual understanding in team designs. From a constructivist perspective of learning, this would be explained as due to greater opportunities to build on prior personal knowledge in a community or learners. By examining social and collaborative facets of learning experiences, we may corroborate that authentic design experiences afford such learning opportunities, and we may be able to better understand how to support students in becoming innovative engineers.

3.4 How do students' perceptions of opportunities to negotiate their own learning relate to the quality of conceptual understanding and innovation in the sponsored design work?

In order to determine whether students perceived that the design class provided opportunities for them to construct their own learning and to productively collaborate, we asked students to rate their prior coursework and the design course using the Constructivist Learning Environment Survey (CLES). This instrument has been validated through several studies [34–37]. The CLES measures *personal relevance, shared control, critical voice*, and *student negotiation,* and provides a picture of the practices as they exist in the classroom (Table 10). The 5-point Likert survey (1 = Never, 5 = Always) was administered individually as a post-test for cohort one and as a pre-test (addressing prior coursework) and post-test for cohort two. An exploratory factor analysis indicated that the grouping of the questions was satisfactory for all but one question ('What I learn has nothing to do with life beyond my classroom setting'). Previous research with more general audiences has not reported this effect, but using a restricted sample of engineers may have led to different findings. Because this question did not group with the others, it was not included in our analysis. There were no differences between cohorts on any dimensions for the CLES when rating the design course.

While all facets of the CLES showed increases (Fig. 3), none of them were statistically significant, due in part to low power and in the case of *student negotiation*, significant unexplained variance in the relationship between prior and design course scores, meaning that other variables impact this relation-

Table 10. Student reported results on the Constructivist Learning Environment Survey

Category	Sample question
Personal Relevance	I learned about the world beyond the classroom setting
Critical Voice	It is acceptable for me to question the way I am being taught
Shared Control	I planned what I was going to learn
Student Negotiation	I asked other students to explain their thoughts

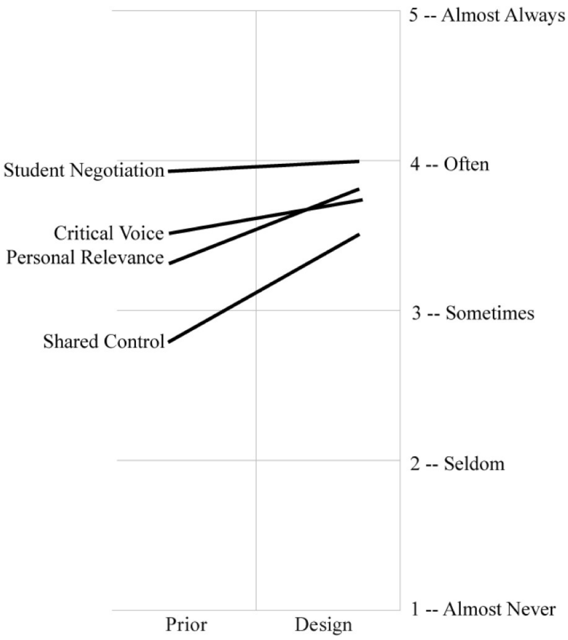

Fig. 3. Ratings on the Constructivist Learning Environment Survey for prior coursework and the design class.

ship. Because this is not the case for the other facets, we only proceed with further modeling for *student negotiation*, incorporating other explanatory variables to account for this variance.

To explain the variance in design class scores for *student negotiation*, we incorporated a team level variable: the expert scores of innovation for the final designs (Table 11). We selected this variable as an explanatory variable because we were interested in modeling innovation and because we hypothesized it should relate to *student negotiation.* We viewed the team as a fundamentally meaningful part of the design learning process. We hypothesized that students who perceived the class as offering few opportunities to negotiate their ideas with their teammates would be in teams producing less innovative designs. To test this hypothesis, we again used a hierarchical linear model, allowing us to incorporate both student and team level variables without increasing the risk of making a Type One error, that is, finding something significant that is not. The student level model includes the students' scores on *student negotiation* for both the design class as the outcome variable and for their prior engineering coursework as a student level explanatory variable (Equation 6). Final innovation scores are included in the team level model as an explanatory variable (Equations 7 and 8).

Level-1 Model: Students

(6) Design *student negotiation*$_{ij} = \beta_{0j} + \beta_{1j}$*(Prior *student negotiation*) + r_{ij}

Level-2 Model: Teams

(7) $\beta_{0j} = \gamma_{00} + u_{0j}$

(8) $\beta_{1j} = \gamma_{10} + \gamma_{11}$*(Final innovation scores) + u_{1j}

The parameters related to student negotiation may be interpreted as follows (Table 12): On average, the *student negotiation* score for the design class was 3.977. The *t* test result suggests that this score is different from zero, $t = 28.314$, $p < 0.05$. On average, students score the design class 0.315 points higher than their prior engineering courses. This increase is not significantly different from zero, $t = -0.707$, $p > 0.05$. Higher scores by experts on final innovation correspond to significantly higher *student negotiation* scores for the design class, $t = 2.395$, $p < 0.05$.

The variance of individual scores for *student*

Table 11. Variables in the Conditional Model

Design *student negotiation* $_{ij}$	Outcome variable; Score for design class on *student negotiation* by student i in team j
β_{0j}	Average score for team j
β_{1j}	Average relationship between design class and prior coursework scores for team j
γ_{00}	Average score
γ_{10}	Average slope for midtest/pretest for cohort one
γ_{11}	final innovation effect on design/prior relationship
r_{ij}	Difference between a student's score and the team average
u_{0j}	Difference between a team score and the average team score

Table 12. Conditional Hierarchical Linear Model of Student Negotiation

Fixed effect	**Coefficient**	**SE**	***t* ratio**	***p* value**
Intercept, γ_{00}	3.977	0.140	28.314	0.000
Prior *student negotiation*, γ_{10}	–0.315	0.446	–0.707	0.489
Final innovation, γ_{11}	0.757	0.316	2.395	0.029
Random effect	**Variance component**	**df**	χ^2	***p* value**
Team level, u_{0j}	0.000	12	9.723	> 0.5
Slope, u_{1j}	0.003	11	12.746	0.310
Student level, r_{ij}	0.867			

negotiation for the design course is not significant. The statistical test result suggests that scores on student negotiation do not differ significantly across students, $\chi^2 = 9.723$, $p > 0.05$. The statistical test result related to team variance suggests that scores do not vary significantly across teams, $\chi^2 = 12.746$, $p > 0.05$. This means that although the teams do not contribute significant variance to individual scores, by incorporating final innovation at the team level, we have sufficiently explained the variance in scores on *student negotiation*.

Essentially, this means that for those students who perceived that the design class provided more opportunities to negotiate, experts tended to score their final designs as more innovative. This would suggest that the interactions within teams were a critical aspect of producing innovative design. These findings indicate that the teamwork in the design course gave the students opportunities to negotiate their ideas with their teammates and that by engaging in an authentic design experience, they were afforded, though may not have taken advantage of, opportunities to negotiate their own learning. This is explored further in our related qualitative work [38].

4. Discussion

In this sequence of analyses, we examined authentic, in-situ design learning in the context of biomedical engineering. Determining how learning experiences should mirror the community of practice can be difficult, but our findings suggest that inducing the need to consider multiple perspectives via voice of the customer was critical to design learning. The voice of the customer served to direct meaningful problem-posing in design, affording students the opportunity to practice asking relevant questions. The authenticity of the sponsored project and of the redesign project helped the students to value the voice of the customer and to understand the intrinsic design requirement of incorporating customer needs. We consider the differences between the cohorts in terms of *problem finding*. Problem finding occurs at the forefront of problem solving. Both cohorts were given ill-structured design tasks, but the questions that framed their efforts differed. The task-as-given is not a solvable design problem, 'the dilemmas do not present themselves automatically as *problems* capable of resolution or even sensible contemplation. They must be posed and formulated in fruitful and often radical ways if they are to be moved toward solution. The way the problem is posed is the way the dilemma will be resolved' [39]. For cohort one, the problems design teams posed focused around how to functionally incorporate a material, and how to make their design differ from prior designs. The resultant problem space is mechanistic and decontextualized, as incorporating the specified material seemed too many of the teams to be needlessly complex and arbitrary. For cohort two, the problems focused on solving customer needs. The resultant problem is more interesting and worthwhile to solve because it is motivated by an understood need or set of needs.

The need for problem finding experience has been called for [39, 40], though research has largely focused on problem solving. This is reflected in many examples of problem based learning activities, which carefully frame the problems for students to solve [41–43]. Research on transfer would suggest that *exposure* to examples of relevant problems would not adequately prepare students to *pose* relevant problems [44–47]. This can be predicted by considering the different skill sets involved in reading, understanding, and solving a posed problem versus understanding a domain well enough to pose relevant problems. Transfer requires sufficient initial learning to occur [48]; without practice posing as well as solving problems, students will not become skillful at posing relevant problems. The redesign activity completed by cohort two gave them experience posing relevant problems and led to more meaningful learning as they began their sponsored projects.

We may further consider the differences between cohorts by considering design from a cognitive stance: research on design expertise has demonstrated that it is composed of two dissociable dimensions: declarative knowledge and procedural knowledge [49]. Declarative (also termed explicit) knowledge is easily articulated, domain specific knowledge. A simple example would be knowing that stepping on a car's brakes will cause the car to slow down and stop. Procedural (also termed implicit) knowledge transcends domain boundaries and encompasses knowledge that is not describable with a single cause-effect rule. Making a judgment about when and how much to apply your foot to the brake in your car is an example of procedural knowledge. These two types of knowledge have a solid neuroanatomical basis [49], but more importantly, can help us to articulate why achieving outstanding factual and conceptual knowledge is not sufficient preparation for engineers.

While it is relatively easy to teach the declarative aspects, which are readily verbalizable, encompassing the majority of the factual and conceptual aspects within a domain, it is difficult to teach the procedural aspects, which include design skills such as making judgments and optimizing a design. Further, far less attention is paid to procedural knowledge. Declarative knowledge is insufficient for good design and this may be a major difference between levels of expertise. Authentic design experiences can help students develop procedural knowledge [49]. Experiences such as the sponsored project and the redesign project provide greater opportunities for learning procedural aspects of design. This was much less true for the preliminary project completed by cohort one. Given that some universities do not have the resources for sponsored projects, this finding has implications for structuring less authentic design experiences: by allowing students some autonomy in identifying, through customer needs, a redesign path, students become authentically engaged in design and therefore have greater opportunities for learning the procedural aspects of design.

Another aspect of authentic design that can be incorporated into more classes is extended teamwork. Research on collaborative learning has shown that students collaborating as they learn (as opposed to teacher-directed or self-directed learning) leads to greater knowledge [50]. Our finding that whereas design conceptual understanding may be predicted with mid-test scores of design skills, design innovation could not be accounted for. We found that when students perceived opportunities to compare their understanding to one another, they tended to be rated by experts as generating more innovative designs, suggesting that teamwork may give students opportunities to practice being innovative when they take advantage of the collaborative potential of a team. This did not occur simply by having students placed into teams, however. We explore this in our related qualitative work [38].

5. Conclusions

This study investigated in-situ student team design learning through a sequence of analyses. Our first question explored how two brief, non-sponsored design projects differently prepared students for an industry sponsored project. We found that in the kit-based version, students did not learn to value or incorporate customer needs, whereas in the redesign version, the design process was driven by customer needs. The latter experience was a more authentic design task because the constraints were intrinsic to the task and the students had to define the design problem based on customer needs.

We also investigated experts' scores on conceptual understanding and innovation of the team design work. We found that for both cohorts having high scores on early conceptual understanding did not correlate to more innovative final designs. This finding—which runs counter to common educational practice—aligns with departments in which design is being taught throughout the curriculum.

Initial scores on a test measuring design skills held no predictive power for later design skills or expert perception of design quality. This finding suggests that many students can benefit from design experience, and is a further argument to consider including design projects earlier in the curriculum. Design affords students the opportunity to construct their own learning and to have greater control over their learning.

Variance in expert scores of final design conceptual understanding was explained by mid-test scores on *team feasibility* and *team voice of the customer*. This shows a link between skills learned in the preliminary design project and the final design project, and clarifies the need for early authentic design activities that provoke students to considering design feasibility and customer needs. We found that variance in expert scores of final design innovation explained variance in individual scores on *student negotiation.* This finding highlights the social interactional nature of design success, and is more deeply explored in our related qualitative work [38]. By giving the students some autonomy in the (re)design process, they were afforded the opportunity to negotiate their own learning in a team, and this corresponded to more innovative design. This learning structure is critical for students who are soon to become autonomous engineers.

Our findings have implications for those interested in teaching design as a backbone, rather than as a capstone; teaching design throughout the engineering curriculum may seem daunting, but every project need not be industry sponsored. By considering outcomes related to the preliminary projects, we found that some projects better supported student learning and engagement than others. The redesign project reflected authentic engineering design practice better than the more kit-like project in consequential ways. In the redesign project, teams had to choose a device to redesign and then rely upon customer needs in order to decide upon a design path. This meant that they had to define their design problem and determine which solution would optimally meet the needs and constraints of their project. This is in contrast to the teams who designed stethoscopes from a kit, who felt that the customer was irrelevant to their process and saw the project as arbitrary. By including an authentic reason for teams to base their design upon customer needs, the students had opportunities to pose relevant design questions. Such experiences help by providing opportunities for learning procedural aspects of design. This has implications for how design is taught, as many departments employ design projects that are more sequestered.

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Appendix A: Example Sponsored Projects

Cohort one

Project	**Advisor field**
Stem Cell Isolation System	Electrical and Computer Engineering
A Novel Concept for the Diagnosis of Heparin-Induced Thrombocytopenia	Biomedical Engineering
Device for the Removal of Carbon Dioxide from Exhaled Breath Condensate	Biomedical Engineering
Medical Equipment Repair, Calibration, and Distribution Facility in Honduras for Central American Medical	Biomedical Engineering
Advanced Infant Temperature Feedback Thermal Environment Control for Portable Incubators	Biomedical Engineering
An Injectable Polymer Scaffold with Mesenchymal Stem Cells as a Repair Device for Annulus Fibrosus	Biomedical Engineering
Design of Metal Nanoparticle Conjugates for Live Cell Molecular Interaction Imaging	Biomedical Engineering
Design of an Adaptive Postural Stability Acoustic Feedback System	Electrical and Computer Engineering

Cohort two

Project	**Advisor field**
Flow Phantom to Simulate Blood Flow in Cerebral Aneurysms for Use with a Clinical Magnetic Resonance Scanner	Biomedical Engineering
Enhanced Vision System	Electrical and Computer Engineering
Feedback System to Optimize Delivery of Vagus Nerve Stimulation Therapy	Biomedical Engineering
Bioresorbable Foam that Maintains Air Permeability During Degradation	Biomedical Engineering
Design and Evaluation of Arthroscopic Delivery Tools of Injectable Hydrogels	Biomedical Engineering
Synthetic Plantar Fat Pad Prosthetic	Kinesiology and Health Education
Prosthetic Leg for Central American Amputees	Mechanical Engineering
Osteovation Bone Void Filler Mixer/Delivery System	Biomedical Engineering

Appendix B: Design Skills Test

This is a very complex problem. A full solution would require extended attention and a number of iterations. However, one of the keys to success in extended problem solving is how you get started. Our goal is to access how you get started on a problem. Your task in this problem is to begin designing the device described below.

In severe trauma patients hypothermia is a common occurrence and issues in a significant increase in mortality. This situation is particularly grave for wounded soldiers for which it has been shown that mortality doubles when the body core temperature reaches a value of 34ºC or lower. Patients suffering from severe trauma tend to become hypothermic regardless of the environmental temperature, and in a war zone, such as the recent US involvement in Iraq and Afghanistan, casualties have suffered hypothermia at a rate in excess of ninety percent. Consequently, the prevention and treatment of hypothermia have been identified as being a major deficiency in American combat medical capability. The Department of Defense is seeking solutions to solving the problem of preventing and treating hypothermia in war casualties. Owing to constraints imposed by the battlefield environment, there are a number of very specific limitations that must be enforced for any possible solution. Rapid evacuation to a Forward Surgical Hospital typically requires five hours and a ride in a cold helicopter. To be effective a warming device must be able to transmit energy to the body core at a rate of 60 watts over the five hour period. It has been determined that the most effective method of delivering heat directly to the body core is via arteriovenous rewarming, being far more efficient than any surface warming technology. The device must be compact, light in weight, and robust (capable of being dropped from a helicopter at 150 feet onto a concrete surface.). The device must contain its own power supply since there is generally not an external electrical service available on a battlefield and during critical phases of transport. Batteries are too heavy and are inefficient. Thus, the energy source of choice for heating is compressed butane which can be used to fire a burner in a small heat exchanger through which a minor fraction of the patient's blood flows. A surgical group has proposed designing a unit capable of warming 300 ml of blood per minute. The pumping source to move blood through the heat exchanger is the patient's heart. Access to the patient's arteriovenous system will be the same as standard practice for a heart lung machine. The proposed device holds tremendous potential for providing life-saving support for trauma patients in both the military and civilian populations. At the present time it is still in the concept and prototyping phase of development. Since the early studies have been accomplished via some ingenious but intuitive work by a team of surgeons, there is no basis for understanding and predicting performance based on a rational model of the device when attached to a patient.

Vanessa Svihla is an Assistant Professor at the University of New Mexico in Teacher Education. She received an M.S. in Geology (2003) and a Ph.D. in Science Education (2009) from The University of Texas at Austin. Her dissertation investigated students in a biomedical engineering class learning to design. Vanessa has taught high school environmental science in the Philippines as a Peace Corps Volunteer, and at the University of Texas, she taught in the geology department and in the natural sciences teacher education program, UTeach. She was a visiting intern at the University of Washington Learning in Informal and Formal Environments (LIFE) Center and completed a post-doc in the Graduate School of Education at the University of California-Berkeley, where she designed and researched assessment integrated within science learning and co-taught video analysis. She serves as the 2011-2012 chair of the AERA special interest group, Learning Sciences. Vanessa applies integrated methods (qualitative analysis, statistical modeling, temporal analysis, and network analysis) towards understanding complex learning in natural settings. She teaches in the secondary licensure program and studies design activity in a variety of settings.

Anthony J. Petrosino is a graduate of Columbia University's Teachers College (MA, 1990) and received his Ph.D. from Vanderbilt University in 1998. He completed a post-doc at the University of Wisconsin where he was a member of the National Center for Improving Student Learning and Achievement in Mathematics and Science (NCISLA). In 1999 he accepted a Professorship at the University of Texas and received tenure in 2004. He holds the Elizabeth G. Gibb Endowed Fellowship in Mathematics Education. Dr. Petrosino has published over 20 peer reviewed journal articles, made over 100 national and international conference presentations and has supervised a dozen doctoral dissertations. He has received over 30 million dollars in grants from the National Science Foundation, the Department of Education and the McDonnel Foundation for Cognitive Studies. He is a founding professor of the nationally recognized UTeach Natural Sciences preservice teacher education program. From July 2007 to August 2009 he served as the Assistant to the Superintendent in the Hoboken School District. His research focuses on children's and teacher's scientific and mathematical reasoning in the context of schooling, with an emphasis on activities and tools for developing thought. This includes the creation and study of learning environments that foster the development and growth of experimentation and inquiry in the elementary and middle school grades. His work has also investigated the types of scaffolds developed within classrooms that support the nature of children's scientific understanding around motivating hands-on activities. A second strand of research focuses on investigating the opportunities for model-based reasoning (the ability to construct and articulate explanations of observable phenomena) that occur in typical science classrooms as students move conceptually from everyday understanding to formalized scientific understanding.

Kenneth R. Diller is a Professor of Biomedical and Mechanical Engineering and the Robert M. and Prudie Leibrock Professor in Engineering at the University of Texas at Austin. He was the founding Chairman of the Department of Biomedical Engineering at UT Austin, UT MD Anderson Cancer Center, and UT HSC Houston, and is also a former Chairman of the Department of Mechanical Engineering. He has studied the application of the principles of heat and mass transfer and thermodynamics to the solution of many different types of biomedical problems. His research has covered a diversity of topics such as the frozen banking of human tissues for transplantation, how burns occur and can be treated, development of new devices and methods for therapeutic hypothermia, control of gene expression during hyperthermic cancer therapy, design of the next generation space suit, and application of the scientific principles of how people learn to the creation of engineering curricula. He has published more than 260 refereed articles and book chapters and written or edited seventeen books on these topics. Professor Diller earned a Bachelor of Mechanical Engineering degree cum laude from Ohio State University in 1966, followed by a Master of Science in the same field in 1967. He was awarded the Doctor of Science degree, also in mechanical engineering, from the Massachusetts Institute of Technology in 1972. After spending an additional year at MIT as an NIH postdoctoral fellow, he joined the faculty of the College of Engineering at the University of Texas as an Assistant Professor and has progressively been promoted to his present position. He was awarded

an Alexander von Humboldt Fellowship from the Federal Republic of Germany in 1983–84 to conduct research on the frozen preservation of pancreas islets at the Fraunhofer Institute at the University of Stuttgart, and a Fogarty Senior International Fellowship from the U.S. National Institutes of Health in 1989-90 for similar studies in the Department of Surgery at the University of Cambridge in England. He has been Editor of the ASME J. Biomechanical Engineering, Associate Editor of Annual Review of Biomedical Engineering and has served on the editorial boards Cryobiology, Intl. J. Transport Phenom., Cell Preservation Technol., Critical Reviews in Biomedical Engineering, and Cryo–Letters. He is a Fellow of ASME, AAAS, BMES, and AIMBE, has been President of The Society for Cryobiology, Vice-President of the International Institute of Refrigeration, Chair of the Bioengineering Division of the ASME and Chair of the College of Fellows of AIMBE. He is recipient of the ASME Heat Transfer Memorial Award for career accomplishments in biomedical heat transfer, the ASME HR Lissner Award for career accomplishment in biomedical engineering, and has been an ASME Distinguished Lecturer.