Chapter XX: Engineering in/&/or/for Science Education

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STEM: I don't know what it is, but I want one

In various policy circles involving state governors, the US congress, or high tech industry leaders interested in education, there has been considerable recent excitement about increasing exposure and performance in STEM: Science, Technology, Engineering, and Mathematics (National Academy of Engineering, 2007). A very serious problem underlies this excitement. Most large companies depend primarily upon new product lines to generate their profits and the US has tied its self-identity to high tech innovation. At the same time, many countries in Europe and Asia have considerably increased their capacities for technological innovation, with some US firms now off-shoring the design work as well as manufacturing. Currently, approximately 90% of the world's engineers live in Asia, and a large, continually increasing proportion of the PhD engineers in the US grew up in Asia. In other words, the US economy and self-identity are at risk.

How did we get here? Salient in everyone's mind is the regular poor showing US children have in international assessments of proficiency in mathematics and science, such as the Trends in International Mathematics and Science Study (TIMSS) and Program for International Student Assessment (PISA). TIMSS is conducted in mathematics and science every 4 years since 1995 with 4th and 8th grade students (occasionally 12th grade) in approximately 40 to 50 countries depending on the grade level and year. There has been some growth in mathematics performance but no growth in science performance in the US over that period. Overall, US children demonstrate above average performance in mathematics at 4th and 8th grades, but are not in the top 5 countries (primarily Asian countries). In science, US students are above average at both grades, but are slipping in relative performance from 4th grade (8th spot) to 8th grade (11th spot). To see how that trend across grades continues, one must look to PISA. Since 2000, the PISA is administered approximately every 3 years to 15-yr-olds in approximately 50 countries (note: while TIMSS focuses on particular grade levels, PISA focuses on particular ages). In both mathematics literacy and science literacy, US students scored below average for all countries, and below most developed countries. In sum, in terms of mathematics and science performance, US children begin high but not at the top, and slowly slide in performance, finishing well below many other developed countries.

Excitement about improving US performance in science and mathematics is not new; similar calls to action can be found in the 1960s and 1980s (National Research Council, 2007, 2009). However, what is new is the broader focus on STEM as a whole, now including technology (the artificial world) and engineering (the way people design it) in the call to action. It is not just about being smart, but about producing adults who are fluent and can innovate with technology. Another important factor is career interest and college degree enrollments. While undergraduate enrollments overall in the US have greatly increased in the last 25 years, enrollments in STEM fields have not grown, and in some disciplines have actually decreased in absolute numbers (National Academy of Engineering, 2007). Overall, US students are simply not that interested in science and engineering careers (National Research Council, 2007, 2009). So, US policy makers need to improve the K-12 setting such that more children are able and willing to pursue high tech careers.

Of the STEM disciplines, engineering is the most poorly positioned in K-12 instruction to obtain more curriculum time. Current reform efforts in the US tend to be focused on mathematics. Performance in mathematics, in addition to English Language Arts, is commonly the primary measure used in the current high-stakes accountability system to evaluate overall district/school performance. Even though other subjects may be tested, they are not given nearly as much weight—and the gains over the last decade by the US in mathematics but not science are consistent with this testing focus on mathematics over science. Only one US state has a clear focus on engineering in their accountability system, and very few children in the US are exposed to engineering at the K-12 level (National Research Council, 2009). For science or technology, one could make the argument that more effective instruction instructional time could produce better outcomes. However, the same argument cannot be made for engineering because it is simply absent in the curricula of most schools. Including engineering within technology education is also a very limited solution because many students do not take any technology education classes and because a very large proportion of technology education teachers are poorly prepared to teach the science and mathematics that engineering methods require (National Research Council, 2009).

Logically, therefore, in the short and medium term, engineering can only see significant gains across the board at the K-12 level if engineering instruction is included within science or mathematics instructional time. That integration can only happen if there is synergy between engineering instruction and science or mathematics instruction; in the given policy context, we cannot trade increases in engineering for decreases in mathematics or science.

The current chapter focuses on exploring this potential synergy. What is the relationship between science and engineering, especially with respect to instructional outcomes? We focus on the case of science-engineering synergy because science instruction is likely more open to revision than mathematics instruction and because more data exist on that pairing. The first half of the chapter is a conceptual analysis of the overlap between science and engineering. The second half of the chapter considers empirical data on the value of applying science processes in engineering design tasks and the value of engineering design tasks for building scientific knowledge and thinking skills.

Conceptual Analysis

Science & Engineering — Competing Epistemologies

At the top level of description as epistemologies, science and engineering are competing rather than similar. Science has an analytic goal: the explanation of natural phenomena. The analysis goal brings a reduction or narrowing to work, with different sciences focusing on different components of larger issues. For example, economists, political scientists, sociologists, social psychologists, and cognitive psychologists interested in educational reform will not only bring different methodologies to the shared broader issue, but they will be attacking variables and phenomena that have little overlap across disciplines (e.g., economists examining dollars spent on various choices, political scientists examining interconnections between policies and voter interest, social psychologists examining the effects of teacher-student interactions on student self-images, and cognitive psychologists examining the relationship between cognitive demands of instructional activities on student learning). Similarly, biologists, chemists, and earth scientists interested in the broader issue of global warming will be investigating different variables and phenomena that have little overlap across disciplines.

By contrast, engineering has a synthetic goal: the creation of artifacts that meet particular needs. The synthetic goal involves integrating a broad amount of knowledge from diverse areas to solve a specific problem. For example, a curriculum development team would need to consider economic, political, social, and cognitive components in order to build an effective curriculum. Similarly, a strategy for burying carbon in genetically engineered rapid-growth tree farms would have to consider the chemistry of photosynthesis, the biology of tree growth patterns, and the interactive effects on the surrounding micro and meso ecosystems, to name just a few factors.

To meet these different overarching goals, science and engineering have evolved different systematic process flows. In both science and engineering, it is understood that the overall process is more complex, iterative, and interactive than simple, linear or cyclical flow diagrams suggest (Klahr & Dunbar, 1988), but nonetheless there are separate steps and they have a rough order. Figure 1 presents components that are commonly mentioned in descriptions of science (1A) and engineering (1B).

FIGURE 1 ABOUT HERE

At this top-level description of component processes, engineering design seems quite distinct from scientific discovery. The goals and major processes differ. Further, it is not just a matter of different terms for the same processes. Consider the two points of maximum semantic overlap: ideation/generate hypothesis and prototype testing/conduct experiment. Other than both being creativity tasks, generating ideas for possible solutions to an engineering problem and generating hypotheses to explain a natural phenomenon are different in many ways. Engineering solutions are relatively concrete and hypotheses are relatively abstract. Engineering solutions must manage very diverse constraints whereas hypotheses can be very narrow from one subdiscipline. Similarly, testing a prototype and conducting a scientific experiment are different. Both can involve precise conditions and measurement tools. But the scientific experiment aims to generate patterns between variables whereas the prototype testing examines whether a particular solution meets required specifications[1]. In addition, there are the parts of the engineering process that are less aligned with the primary science processes, such as requirements documents, concept decision matrices, and optimization. Overall, examination of just the top-level epistemologies suggests that the potential synergy between engineering and science is minimal.

Overlap of the Process, Not of the People

One related red herring is the overlap between engineering design and science within individuals, which has some tricky twists that need to be unpacked. Donald Stokes (1997) wrote a very influential book, called *Pasteur's Quadrant*, arguing that there can be important synergies between basic and applied research within some individuals (see Figure 2). Some individuals (like Niels Bohr) have only the understanding goal associated with basic research—they do not care at all about applications like in engineering. Other individuals (like Thomas Edison) have only the building goal associated with applied research—they do not care at all about implications for understanding the natural world. However, there are also very influential individuals who had both basic and applied research goals that were interrelated and both highly influential. For example, Louis Pasteur is credited with inventing pasteurization and contributing important experimental data to the development of the germ theory of disease (as well as other scientific contributions in biology and chemistry). Stokes argues rather convincingly that Pasteur's applied research directly led to important basic research. That is, Pasteur had both engineering and scientific goals, at different points in time, but with synergy between the goals.

FIGURE 2 ABOUT HERE

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[1] Prototype testing can involve a systematic range of testing conditions to make sure the prototype works under a variety of conditions. However, the goal of this testing is not to find the pattern across the tests, but more of a binary pass/fail overall or the determination of a 'breaking' point.

But how does Pasteur's Quadrant relate to the overlap of engineering and science? Is engineering a way of knowledge creation as well as a way of building objects using knowledge? Or is it just that engineering can lead to new questions that science answers, and sometimes the same people who raise the question also answer it? We have the example of some individuals excelling at two different tasks. Do those data *per se* make the tasks themselves overlapping? Suppose some world-class French Horn players were also world class checker players. That would not imply that checkers and French Horn playing were the same skills. In the Pasteur case, there seems to be substance to the synergy, in that the work on the applied problem led to data that were scientifically important. But does overlap of individuals with synergy of outcomes imply overlap in processes? A person can be a Presbyterian and a business owner. Attending a particular church can provide useful business contacts. But that does not mean that religious worship and business are the same process.

The line between science and engineering within individuals has been complicated by actions of the Nobel Prize committee. Consider the 2009 Nobel Prize in Physics. Two of the prizewinners were Willard Boyle and George Smith "for the invention of an imaging semiconductor circuit — the CCD sensor." The invention is itself an act of engineering design not an act of science. The invention involved physics and likely influenced later work in physics, but the award was not given for the underlying physics developments by Einstein or these later influences on physics (achievements also implemented by other researchers), but rather for the invention itself. Is the Nobel Prize committee just confused in this award, or is there perhaps a deeper synergy that our first analysis has missed?

Computational Parallels Between Science and Engineering

Another way of exploring overlap of processes is to investigate computational considerations because one way cognitive scientists define process overlap is via computational overlap, either at the level of the main function being computed or in the algorithms doing the computing (Anderson, 1990; Marr, 1982).

Figure 3 illustrates that both scientific discovery and engineering design have a sequence of divergent and convergent search processes. In science, there is a task of finding a hypothesis that might account for the data. Here, a broad computational search must be undertaken, potentially considering many different options (Cheng, 1990; Langley, Simon, Bradshaw, & Zytkow, 1987). In engineering, there is the task of generating ideas for possible solutions to the design problem (Campbell, Cagan, & Kotovsky, 2003). Again, the search space is potentially quite large. In both cases, the human problem solver uses heuristics to make the search process more efficient (Klahr, Fay, & Dunbar, 1993). In particular, analogy has been named as a particular process that can guide finding new ideas in scientific discovery (Dunbar, 1997) and engineering design (Christensen & Schunn, 2007; Tseng, Moss, Cagan, & Kotovsky, 2008). Interestingly, studies of engineering and science idea generation processes describe a common computational problem, namely one of getting stuck on an early idea. In the case of science, it is called confirmation bias (Tweney, Doherty, & Mynatt, 1982). In the case of engineering, it is called design fixation (Jansson & Smith, 1991).

FIGURE 3 ABOUT HERE

There are also important parallels within the convergent process of both fields. In science, the problem solver must chose between available hypotheses, selecting the best one. In engineering, the problem solver must choose between available design ideas, selecting the best one. This selection process can be done empirically through experimentation/prototype testing (Schauble, Klopfer, & Raghavan, 1991). Or it can be done conceptually, in science through error minimization in applying different theories (in formulas or models) to data, and in engineering through analysis and optimization on computational models of the to-be-designed object. Overall, at the computational level there appears to be much overlap between scientific discovery and engineering design, but consideration at other levels may help to refine the boundaries and better further hone in on the potential synergies between the two.

Subgoals & The Yin/Yang of Science and Engineering

Another way of expressing the overlap between science and engineering is in terms of a reversible nested subgoal/supergoal relationship. From the perspective of engineering design, scientific discovery can be thought of as a subgoal. As part of the process of designing a solution, the designer may have to analyze data, explain observed prototype failures, and develop models—analysis, explanation, and modeling are very recognizable components of science. Yet from the perspective of scientific discovery, engineering design can also be thought of as a subgoal of science. While trying to make a discovery, the scientist might *design* a hypothesis, *design* an experiment, and/or *design* an instrument (Apedoe & Ford, 2010). Each of these scientific design tasks can be quite complex, and some scientists specialize in those elements. For example, consider the distinction between theorists and experimentalists in many fields (Klahr & Dunbar, 1988) and the complex undertaking of modern instrument design in the natural sciences. The mutual subgoal/supergoal relationship suggests that scientific discovery and engineering design, even when kept largely distinct, may have the potential to motivate each other and build off one another.

Conceptual Analysis Summary

Scientific discovery and engineering design have fundamentally different goals with conceptually distinct epistemologies. Yet, there are underlying computational similarities with interesting overlaps in search heuristics. Further, there are multiple subgoal/supergoal relationships between design and science, and this relationship may be a major source of synergy within individuals who excel at both engineering design/applied science and basic science. But some empirical work must be done to examine the obtained synergies between science and design. Pioneering work by Klahr and Carver (1988) suggests that transfer can be observed in complex processes that have logical overlap, but failures to find transfer are a commonly cited challenge to research on learning (Bransford & Schwartz, 2001).

Empirical Analyses of the Science / Engineering Overlap

We summarize three studies that we have conducted to examine the empirical overlap between science and engineering in terms of strategies underlying successful problem solving and in terms of learning gains in science knowledge and process skill achieved by completing engineering tasks.

Study 1: Strategies Underlying Successful Engineering Design in Students

The seminal work by Tschirgi (1980) suggested that children do not consistently use basic science strategies like vary-one-thing-at-a-time (VOTAT) when engaged with design tasks in which the outcomes of a test have clear desirable or undesirable outcomes (e.g., whether a good cake is produced or not). Follow-up work by Schauble et al. (1991) systematically manipulated within the same physical space whether students were given engineering goals (make a fast boat) or scientific goals (find out what makes boats go fast or slow). They found that students given the engineering goal explored less of the space and made more inferences about causality than students given the science goal. But these projects used settings that were science-centric in that there were pairs of conditions for each ‘test’. Engineering design tests tend not to be done that way, but rather as isolates, which may further reduce the systematicity of search under engineering goals or reframe the search in new ways. Further, the prior work did not examine the relationships between student strategies in design, design success, and student learning.

To examine these issues, we conducted a study using the Earthquake task (see Figure 4). Students are given 54 wooden blocks and are asked to design the tallest structure that will withstand 20 seconds of a simulated earthquake on a table that shakes in two dimensions (left-right, back-forth). In our study (Apedoe & Schunn, 2009), we worked with 59 teams of 3-4 high school students. These students had previously worked together on a multi-week engineering design task in their science classrooms, and thus were familiar with each other in another design context. The teams were given 20 minutes to create the tallest stable structure. They could test as many designs as they wanted and there was a prize offered for the team with the tallest stable structure. The students were videotaped, and we coded the strategies that they used from the video. We also administered a posttest that asked students (individually) to describe design principles regarding what made for more successful designs.

FIGURE 4 ABOUT HERE

What strategies are most useful in this task? Students used a range of different strategies. We wish to focus on two particular strategies: VOTAT and Adaptive Growth. The VOTAT strategy is the one classically associated with scientific reasoning. In theory, by varying only one feature from one trial to the next, students are better positioned to learn what factors matter because they avoid confounds in the experimental data—although it is worth noting that a definition of what constitutes a primitive feature, like in real science, is complex. Adaptive Growth is a common design-oriented strategy found in this task: when the given design fails, make the next one the same height or smaller; when the given design succeeds, make the next one taller. The Adaptive Growth strategy may seem very specific to this particular task, but parallel design strategies have been found in experimental design (Schunn & Anderson, 1999; Schunn & Klahr, 2000).

Table 1 presents the relative use of these two strategies by the high performing teams (who achieved a mean success of 26 stable levels) and the low performing teams (who achieved only a mean success of 4 stable levels). Overall, VOTAT is used much less often than Adaptive Growth by both high and low performing teams. But the height of the highest successful structures did correlate with Adaptive Growth strategy use (r=.33), whereas high and low performing groups do not differ in relative use of VOTAT. There were also a range of other strategies that the low performing teams also used, but no one strategy from this list was associated with poor performance. Thus, we have a simple confirmation that design seems to evoke different strategies from designers, and that these design-oriented strategies are more closely associated with design success than classic scientific reasoning strategies.

TABLE 1 ABOUT HERE

One way of characterizing Table 1 is that it examines the fit of science and design strategies for success in design. This characterization then raises the corresponding science goal question: to what extent do these strategies support learning about factors that matter? Table 2 presents such an analysis. In this task, students discovered a number of design principles that influence the stability of tall structures. Across the top of the table are four design principles that were significantly related to relative strategy use. The cells of the table are the point-by-serial correlations between strategy use by the team and whether the students reported each of these principles or not. Interestingly, we see that both VOTAT and Adaptive Growth were positively associated with what students learned from the design task, but that the two strategies resulted in different knowledge. Thought of another way, the design strategies significantly influenced search through the design space and thus it is not surprising that different kinds of knowledge emerged. Future research is needed to unpack whether this effect stems from emphasizing knowledge (what is clearly deducible) vs. performance (what is semantically crucial) per se or whether it comes from taller structures highlighting different design features. It is also interesting to note that the pyramid/triangle principle associated with the VOTAT strategy is perhaps a more holistic perspective on the more componential principles associated with the Adaptive Growth strategy.

TABLE 2 ABOUT HERE

Study 2: Designed-Based Science Learning and Science Content Gains

A number of researchers have explored the use of design to produce gains in scientific content. One approach is simply a motivational boost. Introduce some application-of-science tasks like engineering design tasks to increase motivational levels in students, but the method of knowledge acquisition remains fundamentally one of science (Hulleman & Harackiewicz, 2009). Another approach is to use engineering design as the method of knowledge acquisition (Hmelo, Holton, & Kolodner, 2000; J. L. Kolodner, et al., 2003; Mehalik, Doppelt, & Schunn, 2008; Puntambekar & Kolodner, 2005; Roth, 2001; Sadler, Coyle, & Schwartz, 2000).

Here we describe one study (Mehalik, et al., 2008) implemented in a range of public urban school schools using measures very typical of traditional knowledge assessments in classrooms and on high stakes tests. If engineering is to go to scale inside science classrooms, it must work under those conditions and produce science knowledge gains evident on such test scores.

This study examined pre-post learning on basic science content knowledge (electricity concepts like voltage, current, and resistance, and their changes in various configurations of series and parallel circuits). Two different curricular units were contrasted: the experimental group used a design-based science learning unit called the Alarm Systems Unit and the control group used a hands-on scripted inquiry unit that is widely used in the US to teach this content.

The scripted inquiry unit taught the concepts through a series of investigations that posed a question, conducted some experiments with simple materials (a circuit board, batteries, wires, resistors, bulbs, and a multi-meter) and guided students to find certain key relationships through worksheets. The curriculum also contained formative and summative assessment items to be used throughout. The school district in question had been using this unit already for many years, and the unit was taught over a 4-month period. Although the unit covered a wide range of electricity/electronic topics, we focused on the basic voltage, current, resistance topics covered during the first 4-to-6-weeks.

The Alarm Systems Unit involved a design project spanning 4-to-6 weeks of instructional time that was used to replace the first 4-to-6-weeks of the scripted inquiry curriculum. The overarching activity was one long design task: to create a prototype of an alarm system (in groups of three or four students) to meet some need in the student's own lives. At the top level, the unit had three main phases: problem definition, prototyping, and communication (see Figure 5), roughly following an authentic engineering design process, which kept students in the primary role of engineers throughout the 6 weeks. The materials space of the Alarm unit was basically the same as the one in the inquiry unit, with some minor change in the particular batteries and addition of a few more variations on indicators and detectors to allow for more variations across student teams (see Figure 6 for example materials used in a student prototype).

FIGURE 5 ABOUT HERE

FIGURE 6 ABOUT HERE

There are three key features of the Alarm unit with respect to its relationship to science learning. First, the bulk of the science content learning happens during the prototyping phase, which occupies about 50 percent of the total time. As is commonly the case in project-based learning, students spent a fair amount of time on other tasks beyond simple content learning. Thus, if this kind of approach is to compete favorably with more traditional approaches, it needs to be especially powerful during the prototyping phase. Of course, it is worth noting that inquiry approaches to science instruction also have significant overhead costs in time.

The second key feature with respect to science learning is the decomposition of the larger prototyping task into sequential design of subsystems. Engineers typically think of artifacts as a system with subsystems, and commonly taught approaches to engineering design emphasize a decomposition of the larger design task into subsystem design (Otto & Wood, 2001; Ulrich & Eppinger, 2008). Thus, this decomposition of the larger design task into subsystems was authentic to engineering design. But it also has important advantages with respect to science learning because it organizes student learning to attend to particular science concepts along the way. In the alarm unit, the students work on three subsystems: power, indicator, and detector (see Figure 5). Each of these three subsystems is necessary to a functioning alarm, regardless of which kind of alarm the students are building (e.g., a touch-down alarm, or a locker alarm, or a pill-minder alarm). And each of these three subsystems involves particular science concepts that must be learned in order to create well-functioning subsystems. For example, the detector subsystem requires that students master resistance concepts and parallel circuits. Thus, the subsystems assure that students must encounter all the critical science concepts and roughly organizes the order of this science learning such that teachers can guide the process and the whole class can build a shared understanding.

The third key feature is what happens during the prototyping of each of the subsystems. Here is where the students learn the science. But how does the prototyping process produce this knowledge? Left to the their own devices, students can often be relatively unsystematic, succeeding in neither design nor science learning. The Alarm unit did provide some structure to this learning, asking students to be reflective designers: carefully documenting each design, explaining the goals of the design, making predictions for outcomes, describing the outcomes, and developing a plan for next steps. Indeed, here is where the supergoal/subgoal relationship of engineering and science come into play. As the students became stuck in achieving engineering goals, they would ask questions about how things work in the fashion of science, analyzing patterns in available data. Of course, the students would rarely conduct systematic experiments as they would in the scripted inquiry class. But as the first study in this chapter showed, knowledge might nonetheless be obtained from such design-based experimentation strategies.

The study was implemented in 26 8th grade science classrooms in a large urban district, with 10 teachers and almost 600 students in the experimental condition, and five teachers and slightly over 450 students in the control condition. The schools involved in each of the conditions were closely matched on student demographics and performance variables (e.g., mathematics and readings scores on high stakes tests).

Both groups took short, paper-based, multiple-choice pre and post-tests that focused on basic understanding of electricity concepts that were the primary focus of the scripted inquiry instruction. On these tests, experimental condition students showed over twice the pre-post gains as the control condition students, with a large effect size, d=0.89. This result was especially surprising given that the control condition students nominally spent more time on science learning than the experimental condition students. One teacher chose to split her own sections and used the embedded assessments found in the scripted inquiry curriculum as the measure of learning. Even on this measure that is tightly aligned to the scripted inquiry curriculum, students in the experimental condition heavily outperformed students in the control condition.

The results of the first study provide some explanation for how students in the experimental condition were able to make some gains in science knowledge: design strategies can produce knowledge. However, there is still the mystery of why students in the experimental condition learned significantly more science with noticeably less time on science learning. Here we believe that student motivation levels were likely very important. Many of the teachers reported that student motivation levels were much higher with the design unit than in their previous years of instruction with the scripted-inquiry unit. From this study alone, we do not know whether design-vs.-science was the key to increasing motivation, or whether other differences between the units might have been key—for example, salient features with respect to student motivation levels might be tight scripting vs. more open-ended tasks, or sequence of smaller tasks vs. one larger task. However, one recent study suggests the opportunity to think about practical applications of knowledge *per se* has large motivational benefits in science classrooms (Hulleman & Harackiewicz, 2009).

Study 3: Design-Based Science Learning and Science Process Gains

The results from Studies 1 and 2, as well as results from other labs using design to teach science content, suggest that science content knowledge can be acquired through design processes. Which content is acquired likely depends upon the strategies used by the designer and the part of the conceptual space exposed by those strategies in the given design space. But what about science process skills? Students are expected to also learn the processes of science, especially the skills related to what kinds of evidence provides ambiguous vs. unambiguous support for a given conclusion. Given the different fundamental epistemologies and overall procedures of practice in engineering and science, one might worry about whether students will make any progress in science reasoning skills from design experiences, or perhaps, even worse, show decrements due to mismatching practices. True negative transfer is not usually obtained (Singley & Anderson, 1989), but that may depend upon whether the children clearly view the situations of science and engineering as different. If engineering methods are taught in science classrooms AND engineering methods clash with science methods, then negative transfer might occur.

A few studies of students engaged with design tasks suggest that students' reasoning often does not look very science-like (Roth, 2001; Schauble, et al., 1991). However those studies did not provide much scaffolding on good engineering practices; we would not expect solid reasoning processes in a science task with students provided little instruction on good scientific practices (Kuhn, 1989, 1991). So, our question then becomes: with instruction in good engineering practices, does the experience with an engineering task provide gains or losses in scientific reasoning skills? In the Learning By Design curriculum, there was some evidence of improvements of scientific reasoning skills (Kolodner, Gray, & Fasse, 2003). However, that study was conducted in upper and middle income settings and the measures were not typical pen-and-paper assessments that drive district decision making—it is important to show how the impact will scale more broadly across settings and on measures that are more typically used.

We conducted a follow-up study using the Alarm unit again, but this time focusing on process gains (Silk, Schunn, & Strand-Cary, 2009). We used a pen-and-paper multiple choice test based on previously validated measures of scientific reasoning (Lawson, 1987) and from the Third International Mathematics and Science Study released items. Based on our more detailed analysis of science and engineering practices having supergoal/subgoal relationships, we did not expect to find such negative transfer and, in fact, expected to find positive transfer.

Our primary method was to simply look at pre-post gains on this measure in students implementing the Alarm unit. However, to provide some context for any observed gains, we also compared to pre-post gains observed in another study using two other science curricula: a new inquiry-based curriculum that was previously shown to outperform other inquiry-curricula on gains in reasoning skills and a textbook-based curriculum. As one does not expect to see much reasoning gains from a textbook approach, we actually collected pre-test data at the end of 6th grade and post-test data at the end of 8th grade for the students in the textbook condition, whereas the design and inquiry groups had the pre-test in the middle of 8th grade and post-test at the end of 8th grade.

Figure 7 presents the mean performance in each group. Most importantly for the current question at hand, we see pre-post gains in scientific reasoning scores in the design group, rather than no effect or even reduced scores. However, this figure presents a few other interesting results of relevance. First, the students in the design group were very close to chance performance on the test at pre-test. The students were 73% traditionally underserved minorities and 82% low social-economic status, and both of these factors are frequently predictive of science test scores for a variety of reasons. But these students had also experienced 7 and half years of hands-on science in this district. In only a few months of experience with the design unit, they appear to have made more progress on scientific reasoning than in the previous 7 or so years of science instruction.

A second interesting feature of the data in Figure 7 that the gains in the design group were similar to the gains in the inquiry group and larger than the gains observed in the textbook group even though the textbook group experienced two years of instruction. It is worth noting that students in the inquiry group were from a more affluent setting and this likely explains the higher pre-test scores, but also makes the equivalence in gains between this inquiry condition and the design group all the more impressive.

FIGURE 7 ABOUT HERE

General Discussion

In this chapter, we have presented a detailed analysis of science and engineering to suggest that they have important differences in overall goals and storyline, and important similarities in underlying processes. Further, we have presented data to show that engineering design activities can produce scientific content knowledge and gains in scientific reasoning skills.

FIGURE 8 ABOUT HERE

How can these analyses and results be reconciled? From similarities in underlying processes, we expected to find gains in learning that will transfer based on the seminal work of Klahr and Carver (1988) showing that programming experiences led to general debugging skills that could be applied to non-programming tasks with similar debugging processes. Thus, if engineering involves some pattern explanation tasks as subgoals, then students engaged in engineering activities should make progress on those skills and show evidence of such progress on measures of the logic of pattern explaining (i.e., measures of scientific reasoning), and measures of particular pattern explanations (i.e., measures of science content knowledge). Indeed, as shown in Figure 8, we have often organized our designed based learning materials around a combined design-science learning cycle (Apedoe, Reynolds, Ellefson, & Schunn, 2008; Ellefson, Brinker, Vernacchio, & Schunn, 2008). As students work on the design of each subsystem, they need to engage in scientific reasoning activities to develop a better understanding of the science that supports that subsystem design. In sum, we make explicit the distinctions between the epistemologies and skills of scientific discovery versus engineering design, but actively encourage their connections.

But the differences in goals and storylines can also produce differences in learning outcomes. We found that design involves different strategies that can change which scientific content knowledge is acquired. Further, we saw that many students, especially students traditionally showing poor performance in science classrooms, found the design activities more interesting and motivating, and these motivational benefits could themselves produce secondary gains in science content and skills.

Now, returning to the issue of STEM: can we hope for real gains in science, technology, engineering, and math in the current educational context? From our experiences, we do have some optimism for the possibility of gains in engineering via science classrooms because of the apparent positive results for science from such inclusion. How such synergies will develop for technology and math remain to be seen, but our current work has attempted to make explicit some of those connections (Silk, Higashi, Shoop, & Schunn, 2010; Silk, Schunn, & Shoop, 2009). At the same time, we are working on the development of more design-based learning units in a range of disciplines at the high school level that try to simultaneously make progress on learning of science, engineering, and technology concepts (Apedoe, et al., 2008; Ellefson, et al., 2008).

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Table 1. Relative use of VOTAT and Adaptive Growth by high and low performing teams.

Strategy	High Performing Teams (26 levels)	Low Performing Teams (4 levels)
VOTAT	24% of trials	19% of trials
Adaptive Growth	74% of trials	48% of trials

Table 2. Point-by-serial correlations between relative degree of strategy use and endorsement of design principles.

Strategy	Pyramid/ Triangle	Compact	Wide Base	Narrow Top
VOTAT	0.55*	0.60*	-0.05	0.09
Adaptive Growth	0.03	0.00	0.55*	0.38*

*=p<.05

Figure 1. Typical processes included in descriptions of A) scientific discovery and B) engineering design.

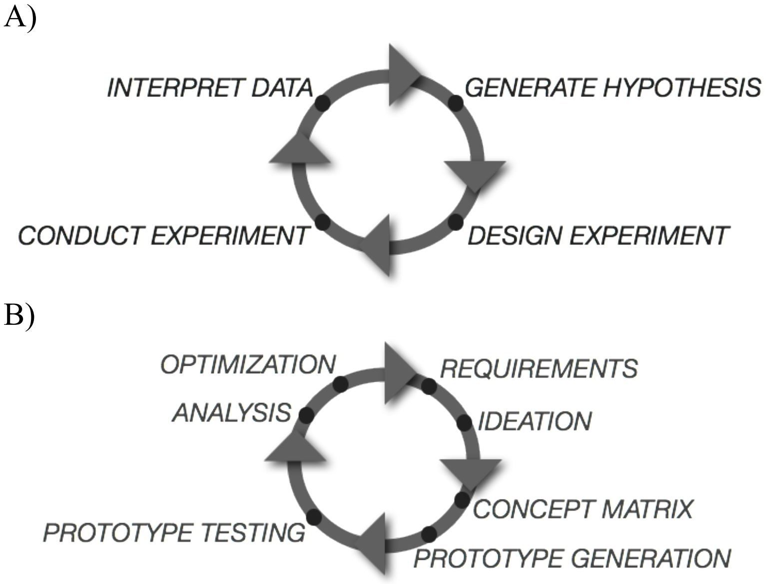

Figure 2. The four quadrants from Stokes' analysis with example individuals in each quadrant of basic/analytic goal by applied/synthetic goal.

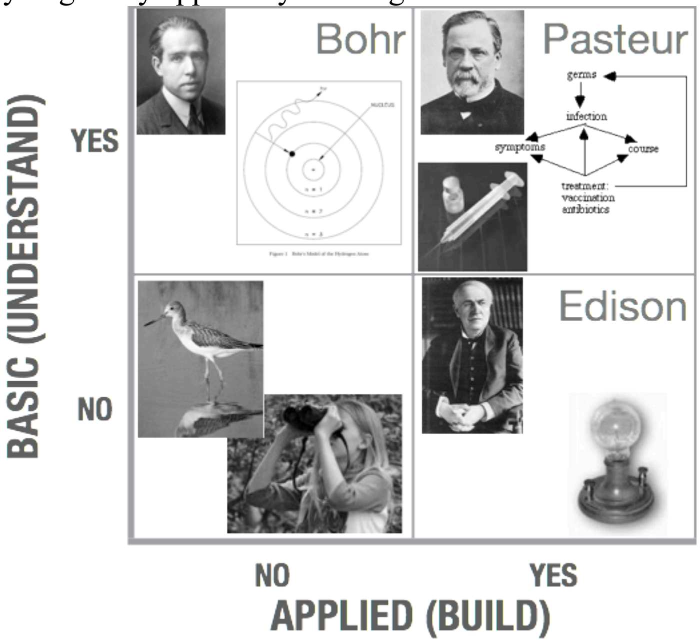

Figure 3. Parallels between the computational processes and process problems in scientific discovery and engineering design.

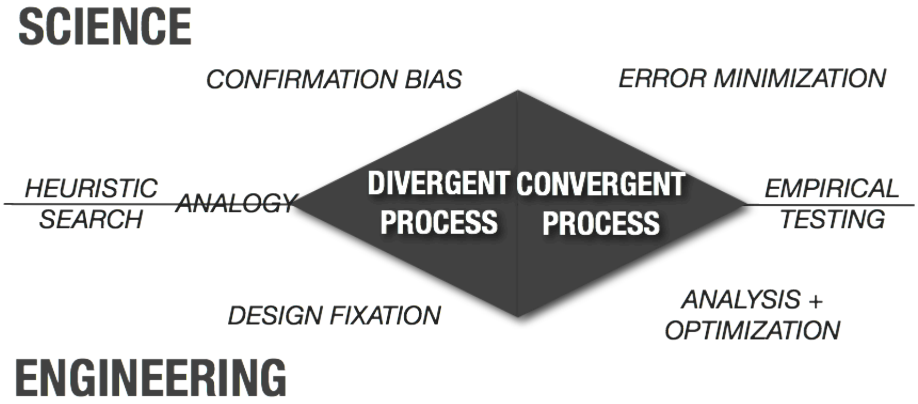

Figure 4. Earthquake task example student design.

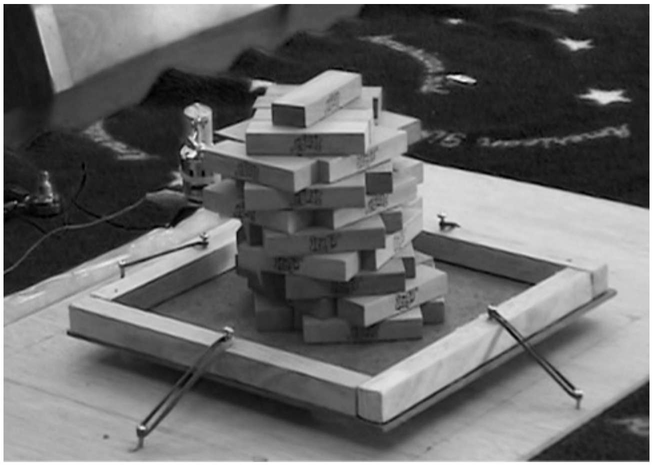

Figure 5. The overall storyline of the Alarm Systems Unit.

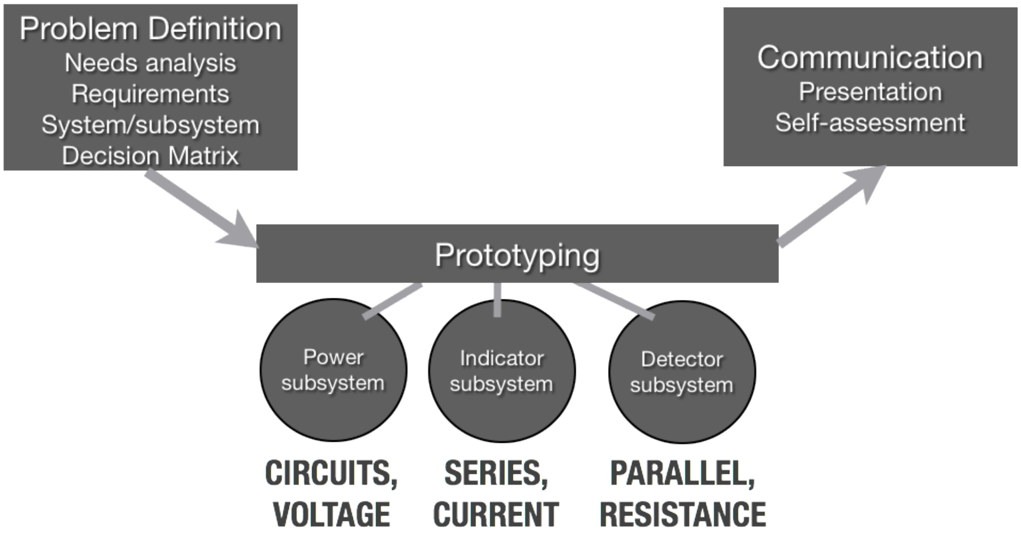

Figure 6. Example materials in a student-designed alarm system. This example includes a buzzer in the upper left (indicator subsystem), an on-switch in the upper right, the "gate" switch in the lower left (detector subsystem), and a battery pack in the lower right (power subsystem).

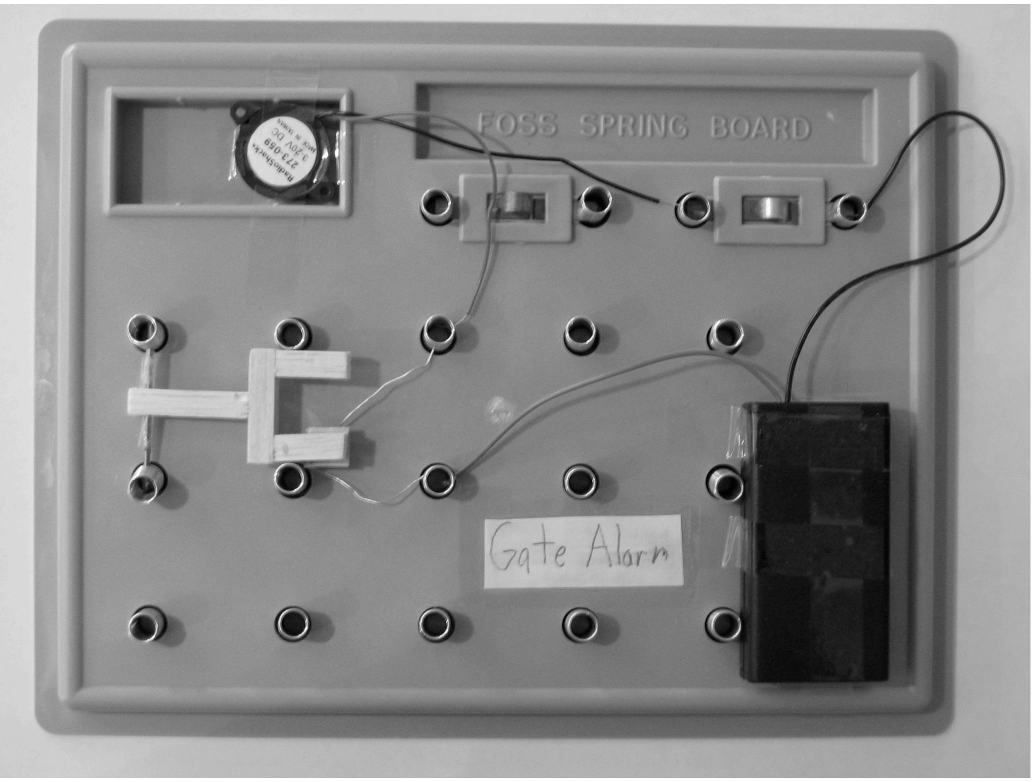

Figure 7. Mean scientific reasoning performance pre and post-test in each of the 3 groups.

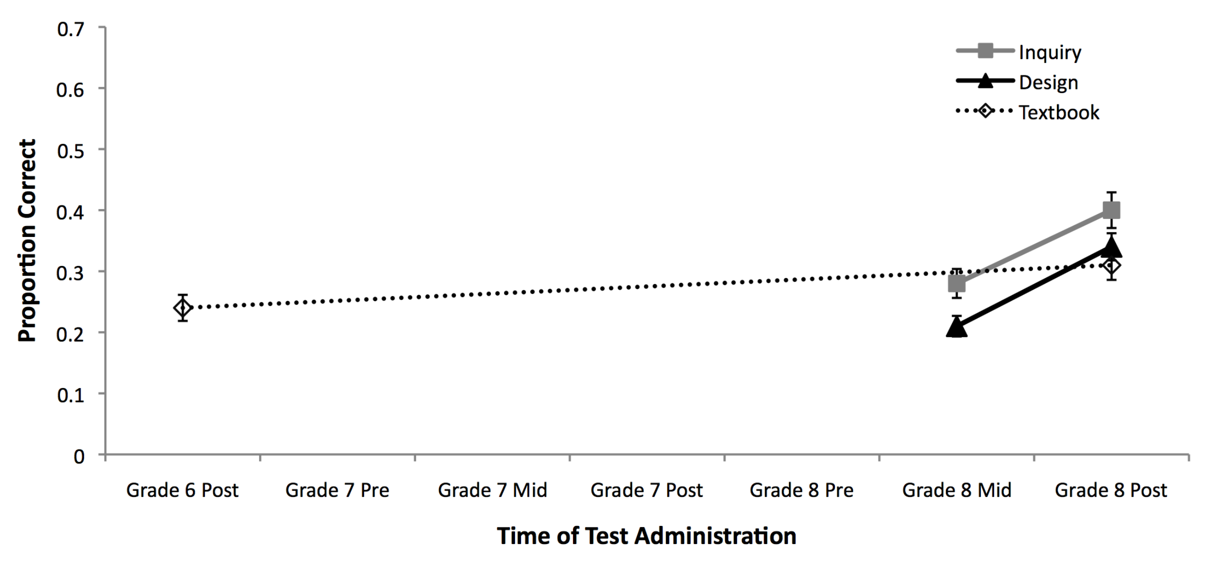

Figure 8. The design-science learning cycle that connects design and science activities.