COLLABORATIVE RESEARCH: LARGE-SCALE RESEARCH ON ENGINEERING DESIGN BASED ON BIG LEARNER DATA LOGGED BY A CAD TOOL

THE NEED

Our understanding of what K-12 students learn from engineering design is limited (Katehi, Pearson, & Feder, 2009). A 2008 literature review concluded that many K-12 engineering education projects lacked data collection and analysis to provide reliable evidence of learning (Svihla & Petrosino, 2008). The Committee on Standards for K-12 Engineering Education found “very little research by cognitive scientists that could inform the development of standards for engineering education in K-12” (National Research Council, 2010). This proposal responds to these problems by introducing educational data mining and learning analytics (Bienkowski, Feng, & Means, 2012) into K-12 engineering design research.

In the context of K-12 science education, engineering design is a complex cognitive process in which students *learn* and *apply* science concepts to solve open-ended problems with constraints to meet specified criteria. The complexity, open-endedness, and length of an engineering design process often create a large quantity of learner data that makes learning difficult to discern using traditional assessment methods. For example, a pattern that looks like “gaming the system” in an inquiry activity (Baker, Corbett, & Wagner, 2006) may be a legitimate search in a vast problem space for meaningful alternatives in a design project. An idea that sounds ridiculous initially may lead to the most creative design at the end. Students may learn more from failed designs than from successful ones because failure promotes the need to explain and revise. The focus of engineering design assessment is not simply on whether or not students “get the right answer,” but on how they acquire science and engineering knowledge and skills in the quest for optimal design solutions. Engineering design assessment thus requires innovative solutions that can track and analyze student learning trajectories over a significant period of time. Sophisticated data mining technologies originally developed for scientific and business applications provide such solutions.

PROJECT GOAL, RESEARCH QUESTIONS, AND PLANS

How secondary students learn and apply science concepts in engineering design processes is one of the most fundamental research topics in learning sciences. Although previous research suggests that engineering design is an effective pedagogical approach to promoting science learning (Apedoe, Reynolds, Ellefson, & Schunn, 2008; Hmelo, Holton, & Kolodner, 2000; Kolodner, 2002; Kolodner, et al., 2003; Mehalik, Doppelt, & Schunn, 2008; Schnittka & Bell, 2011), there are also concerns about the so-called “design-science gap” (Vattam & Kolodner, 2008) that fails science learning in design projects (Apedoe & Schunn, 2013). To expand the research foundations for understanding and solving this problem, the Concord Consortium (CC) and the School of Engineering Education at Purdue University will conduct a large-scale study based on a unique educational technology that we have developed. The project will engage secondary students to use Energy3D, a computer-aided design (CAD) software tool, to design energy-efficient solutions for the built environment based on thermodynamics and heat transfer concepts as well as the engineering principles required by the Next Generation Science Standards (NGSS) ETS1 (Achieve, 2013). The datasets to be collected will be large in two ways. First, over 3,000 students from diverse socioeconomic backgrounds in Indiana and Massachusetts will participate in this project. Second, each design challenge will require 5-7 hours of classroom time to complete. Throughout the entire design process, Energy3D will automatically log and sort all user actions, electronic notes, and design snapshots (collectively referred to as **process data** hereafter) of each student at an extremely fine-grained level. Based on our pilot studies in the classroom, these process data usually sum up to 20 megabytes at the end of a design project for a single active student.

The process data are critical to explaining student learning outcomes and effects of interventions. But the process data are so complex and large that they offer little clue at first glance. To probe deeply into student learning, this project will develop, refine, and apply a set of computational techniques to analyze these large, high-dimensional process datasets. These techniques (collectively referred to as **process analytics** hereafter) will quantify each individual student's learning progress and provide a holistic method to assess his/her performance. For example, these process analytics will be used to detect iterative cycles in a design process, measure the design space explored by a student, gauge the extent and effect of scientific inquiry throughout a design process, and diagnose the bottlenecks that prevent students from completing design tasks and reaching learning goals. Some of these analytics will be the computational counterparts of traditional performance assessment methods based on student articulation, classroom observation, or video analysis (Atman, et al., 2007; Purzer, 2011; Purzer & Fila, 2013). Combining these process analytics with pre/post-test results (Figure 1) and demographic data, this project will address research questions (RQs) related to the "design-science gap" from the following three aspects:

- **RQ1: Patterns and relationships in engineering design processes**: What are the common patterns of student design behaviors and how are they associated with prior science and engineering knowledge, project duration, design performance, learning outcomes, and demographic factors?
- **RQ2: The effect of engineering design processes on science learning outcomes**: How do students deepen their understanding of science concepts involved in engineering design projects? For example, to what extent does design iteration contribute to science learning?
- **RQ3: The effect of scientific inquiry processes on engineering design outcomes**: How often and deeply do students use (simulated) scientific experimentation to make a design choice? To what extent does experimentation trigger students to revise a design or add a new feature?

This research is planned as follows:

- **Advance the data collection capability of a CAD platform to create a "gold mine" of educational data.** This project will expand the logging capacity of Energy3D to generate more varieties of learner data that will provide inputs to powerful data mining tools (Romero, Ventura, Pechenizkiy, & Baker, 2010). The objective is to transform the CAD software into an open, versatile experimental platform to serve data-intensive research on engineering education.
- **Generate the research data and develop the process analytics.** The research data will come from 1) process logging by Energy3D, 2) pre/post-tests of science and engineering knowledge, 3) demographic surveys, 4) classroom observations, 5) expert evaluation of design processes and artifacts, and 6) post-project student interviews. Datasets 4-6 will only be collected from a limited number of randomly selected students for case studies, instrument calibration, and quality assurance. The process analytics will include, but will not be limited to, time series mining (Esling & Agon, 2012; Fu, 2011; Xie,

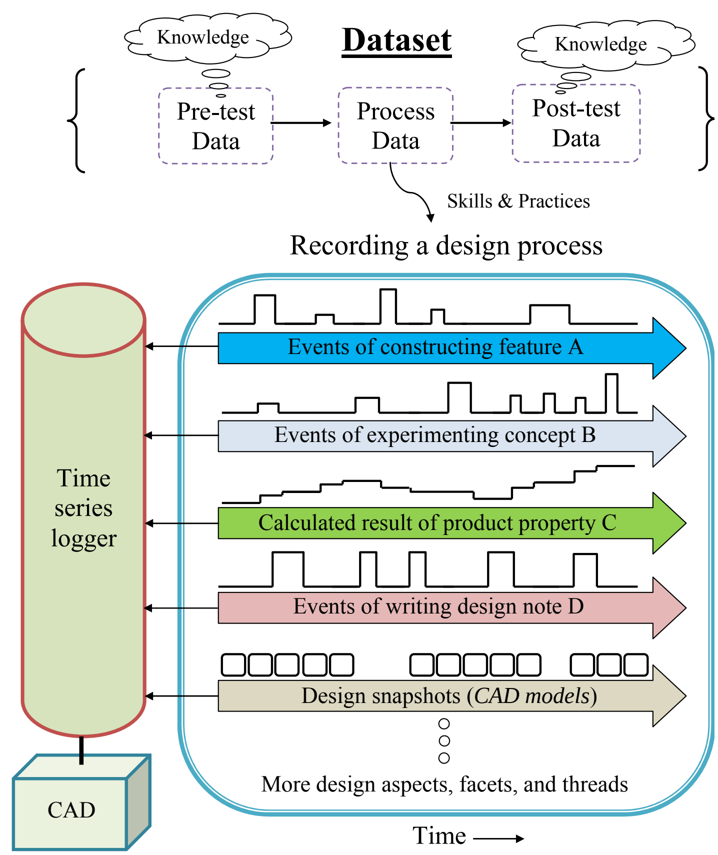


Figure 1. The research design includes pre/post-tests and process mining. Engineering design using a CAD tool consists of many human and computing subprocesses that can be recorded as time series. Analyzing these time series would reveal how students solve engineering design challenges from multiple aspects and how different subprocesses are correlated.

Zhang, Nourian, Pallant, & Hazzard, 2013), association rule mining (García, Romero, Ventura, Castro, & Calders, 2010), and combined action-note analysis (defined on page 12). Some of the algorithms will be based on existing open-source, general-purpose data mining libraries such as SPMF (Fournier-Viger, 2013) and ProM (van der Aalst, 2011). The pre/post-tests will measure student prior knowledge and learning gains resulting from solving design challenges. The pre/post-test results will be integrated with the process data to identify relationships between actions and knowledge and provide explanations of learning outcomes. As the complexity of these datasets often exceeds what common graphing tools can handle, we will also create visual mining tools (Mazza, 2010) to help researchers and teachers understand the results.

- **Calibrate the research tools and validate the research design.** We will carry out six small-scale classroom studies (two rounds for each of the three design challenges, which are described on page 7) in Years 1-2 to calibrate the research instruments and the process analytics. Each study will involve a class of students. The Informed Design Teaching and Learning Matrix recently synthesized by Advisory Board member Crismond and Co-PI Adams based on a meta-analysis of literature (Crismond & Adams, 2012) will be used to validate the research design and the process analytics. The Matrix defines nine engineering design strategies and associated patterns that contrast beginning versus informed design behaviors. A subset of them will be used to test the analytics.
- **Collaborate with teachers to scale up the research to 3,000 students.** Each year in Years 3-5, over 1,000 students will be recruited to solve one or more design challenges selected by their teachers. We will offer workshops to participating teachers prior to classroom implementations. At the workshops, teachers will learn about the research purpose, the design challenges, and the supporting technology. Each teacher will go through the design challenges and the instructional materials. At the end of the workshop, each teacher will have decided which design challenge(s) will be used in his/her classroom. Since several teachers have expressed their interest in tracking student learning (see the letters from Bastoni, Erbland, Iarrapino, and Weathers), the workshops will also provide methods for them to evaluate and visualize existing process data. After the classroom implementations, the teachers will also be invited to join another workshop that focuses on validating, analyzing, and interpreting the data collected from their own students.
- **Apply the process analytics to large datasets.** While the large-scale data collection is underway in Years 3-5, the team will start to analyze the datasets as soon as they are available. The process analytics will continue to be refined as needed. Essential process data will be extracted from sequences of design snapshots. All the results obtained from the process analytics for each student will be sifted and aggregated to a database for statistical analysis to reveal patterns and trends across student groups (e.g., by age or gender) and knowledge domains (e.g., by pre-test scores on individual science concepts). A computer program will be written to automate these data mining procedures.
- **Disseminate project results.** All the datasets collected by this project will be redacted to remove confidential student information and made available to anyone who is interested in mining them but does not have the resources to repeat the process of data production. A copy of these datasets will also be submitted to the Pittsburgh Science of Learning Center DataShop, the largest public repository for data on the interaction between learners and educational software (Koedinger, et al., 2010). This will be the first engineering entry in the repository. The research findings of this project will be published in journals and presented at conferences. We will also hold teacher workshops to disseminate the implications of these findings to K-12 engineering education.

RATIONALE

In engineering design projects, students practice science as they gather and analyze data through experiment-based inquiry and apply this knowledge to conceive, compare, and optimize solutions. Practicing science is one of the most important goals of K-12 engineering education, which is now part of the NGSS. A problem commonly observed in K-12 engineering design projects, however, is that students often reduce engineering challenges to cookbook procedures or craft activities that result in superficial science learning (Crismond & Adams, 2012; Hmelo, et al., 2000). This project will delve into fine-grained process data to systematically identify bottlenecks in design processes that pose difficulties for students to apply science. For the findings to be widely applicable, this research will collect data at a scale unprecedented in engineering design research.

Limitations of Previous Research Methods for Studying Engineering Design

To assess student performance in engineering design projects, researchers have developed several techniques. For instance, verbal protocol analysis was used to obtain data from "thinking aloud" (Atman & Bursic, 1998; Ericsson & Simon, 1993). Latent semantic analysis was used to parse design documentation to characterize designer performance (Dong, Hill, & Agogino, 2004). Timeline analysis was used to monitor students' time allocation to different tasks and their transitions during a design session (Atman, et al., 2007; Atman, Deibel, & Borgford-Parnell, 2009). These techniques have limitations, however. For example, the verbal protocol method is intrusive to classroom activities and is weak in capturing non-verbal processes such as perception and intuition that are so important in design (Lloyd, Lawson, & Scott, 1995). Researchers also found that students did not always put their verbalized knowledge into design practice (Atman, Kilgore, & McKenna, 2008), leaving considerable ambiguity in their performance assessments. The document analysis method has similar weaknesses to those of the verbal protocol method because it, too, is based on analyzing students' descriptions of their work, rather than their actual actions. The timeline method visualizes patterns of time usage on different phases using Gantt charts, but due to the lack of details about the quality of the design subprocesses in the allocated time, time on task does not always reflect designer performance. Another common disadvantage of these methods is that they all require time-consuming data collection and analysis procedures that limit the scale of research. These procedures are often executed manually and the requirement of inter-rater reliability multiplies the work load.

Integration of Computer-Based Assessment and Computer-Aided Design

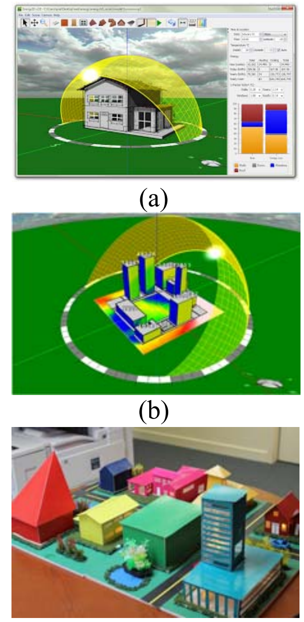
Information technology provides a cost-effective solution to scale up educational research. As an important trend in the field (U.S. Department of Education, 2010), computer-based assessments have been used to study inquiry with interactive media and games (Clarke-Midura, Dede, & Norton, 2011; Gobert, Sao Pedro, Baker, Toto, & Montalvo, 2012; Horwitz, 2011; McElhaney & Linn, 2011; Sao Pedro, Baker, Gobert, Montalvo, & Nakama, 2012). But rarely have they been exploited for assessing design, a process that includes inquiry but is fundamentally distinct in many ways (Lewis, 2006). We see an exciting opportunity to introduce computer-based assessments into research on engineering design. This is possible because computer-based assessments can be implemented within computer-aided design tools.

In workplaces, engineering design is supported by modern CAD tools capable of virtual prototyping—a full-cycle process to explore a complete product on the computer before it is actually built. In classrooms, such CAD tools allow students to take on a design challenge without regard to the expense, hazard, and scale of the challenge. They provide viable platforms for teaching and learning engineering design, because a significant part of design thinking is abstract and generic, can be learned through designing computer models that work in cyberspace, and is transferable to real-world situations. Negative side effects of using CAD tools in engineering education previously reviewed by some authors (Brown, 2009), such as circumscribed thinking, premature fixation, and bounded ideation (Robertson & Radcliffe, 2009), can be mitigated by embedding scientific simulations in CAD to stimulate imagination and iteration.

THE RESEARCH PLATFORM

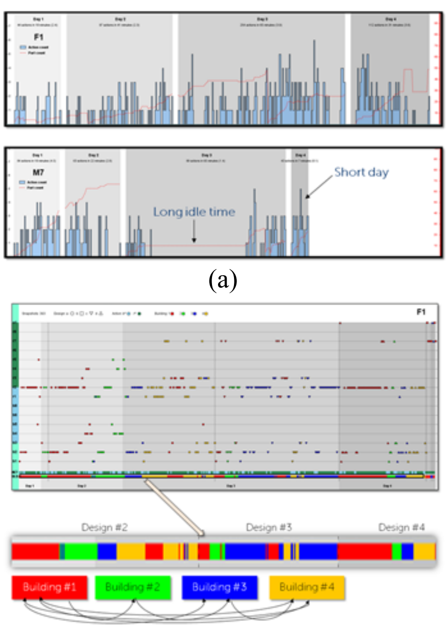
For engineering education research, the advantage of moving a design project to a CAD platform is that **learner data can be logged continuously and sorted automatically behind the scenes** while students are solving design challenges. This data collection technique is promising because the logged human-computer interactions, intermediate design artifacts, and student electronic notes encompass rich information about the quality of learning processes and the evidence of learning outcomes. In a sense, the logs *reflect* students' design thinking and decision-making processes, which are not only assisted by the CAD tool but also regulated by interventions outside it such as brainstorming and instruction. This instructional sensitivity of CAD logs has been confirmed in a June 2013 field test involving 70 high school students and will be examined more systematically in the calibration studies planned in this project.

Energy3D, our open-source computer-aided design and fabrication tool for K-12 students to make scale model buildings, will provide the research platform for this project. The software offers a simple 3D graphical user interface for drawing buildings (Figure 2a) and evaluating their energy performances using solar and heat simulations (Figure 2b). It allows students to "print out" a design on paper, cut out the pieces, and use them to assemble a physical model to extend learning to the real world (Figure 2c). It includes a notepad for students to describe their work while they are designing. Our classroom tests involving 280 high school students showed that most students were able to master this tool within 15 minutes after watching a short demo and could quickly sketch up simple buildings. Over time, they could produce a great variety of designs. No evidence was found that students just duplicated an example or copied one another's design.



(a) (b) (c)

Figure 2. (a) Energy3D: a CAD tool for designing model buildings. (b) Solar urban planning using the solar simulator in Energy3D. (c) A collection of paper buildings "printed out" by Energy3D.



(a)

(b)

Figure 3. (a) The Manhattan plots of time series of total actions: A comparison between an engaged and a disengaged student. (b) Dotted chart analysis of action time series showing iterative design cycles of a student in the Solar Urban Planning Project.

Unlike other CAD tools developed mostly for engineering applications, Energy3D was created from scratch with a vision to support data-intensive engineering education research. We have accommodated data mining in the software architecture throughout the development process. For example, upon receiving an undoable action, the Undo Manager of Energy3D will signal the logger to record it. As a result, Energy3D is capable of logging all actions, notes, and snapshots unobtrusively in the background. These learner data can be used to reconstruct the entire design process with all the important details restored for analysis. The snapshots (computer models, *not* images) can be played back just like running a slide show. Student notes (text strings) to explain or reflect on their designs can also be replayed synchronously to their design actions such that we can coordinate the analyses of *what they did* and *what they thought*. The reconstructed process is native to Energy3D, meaning that each snapshot can be arbitrarily manipulated and examined using all the design and analysis functionalities of the software. This ability to post-process a recorded process to extract any information provides researchers considerable flexibility in data mining. This feature is essential to the study of design as its open-endedness may lead to creative, unconventional results not foreseen by researchers.

We have also developed a basic data visualization tool to render complex results and support visual mining. For example, the dotted chart in Figure 3 shows the spread of actions over time by plotting a symbol for each action (Trčka, Pechenizkiy, & van der Aalst, 2010). The chart has four dimensions: the horizontal axis shows time, the vertical axis shows action type, the color of a symbol represents the object the action is applied to, and the shape of the symbol represents an alternative design solution. These high-dimensional data can be projected onto a selected axis that measures a facet or unfold a thread of the design process, as shown in the lower part of Figure 3b.

With these powerful technologies, we have proven the concept of using a CAD tool as a viable data mining platform to support engineering education research. Our pilot study with high school students solving a solar urban design challenge showed that Energy3D logs can be used to measure the level of student engagement, reveal gender differences in design behaviors, and distinguish the iterative and non-iterative cycles in a design process (Xie, et al., 2013). To the best of our knowledge, this was the first time that gender differences in engineering design reported in many previous studies (Kimbell & Stables, 2007) were observed through educational data mining. We are confident that the proposed project will result in many more original discoveries.

BROADER IMPACTS

This project will contribute to the emerging fields of educational data mining and learning analytics (Bienkowski, et al., 2012) through the proposed research on one of the most complex STEM practices—engineering design. The large scale of this study will allow for much greater representation of student diversity not attainable in small-scale studies, thus resulting in broader implications of its findings to the adoption of the new science standards that extensively include engineering design.

The project will expand “evidence approaches” for digital learning (U.S. Department of Education, 2013) using large datasets from students’ engineering design processes. Many earlier studies profiled learners by analyzing traffic data logged by learning management systems. However, those data provide limited evidence of deep learning related to the subject matter. This project will broaden the scope of data mining to assess student learning through complex engineering design projects. It adds to a category of data mining that attempts to derive evidence of learning from tracking student exploration *within* the problem space (Carberry, Hynes, & Danahy, 2013; Sao Pedro, et al., 2012). This type of learner data supports more meaningful assessments as they are more intimately linked to disciplinary concepts and skills.

Fine-grained CAD logs possess all four characteristics of *big data* (IBM, 2012): 1) **High volume**: Students can generate a large amount of process data in a complex open-ended project that involves many building blocks and variables; 2) **High velocity**: The data can be collected, processed, and visualized in real time to provide students and teachers with rapid feedback; 3) **High variety**: The data encompass any type of information provided by a rich CAD system such as all learner actions, events, components, properties, parameters, simulation data, and analysis results; and 4) **High veracity**: The data must be accurate and comprehensive to ensure fair and trustworthy assessments of student performance. These big data have the potential to yield direct, measurable evidence of learning at a statistically significant scale. Automation will make this research approach highly cost-effective and scalable. Automatic process analytics will also pave the road for building adaptive and predictive software systems for teaching and learning engineering design. Such systems, if successful, could become useful assistants to K-12 science teachers. As a result of this project, some of the analytics will be built into Energy3D to provide instantaneous metacognitive feedback to students. This will directly benefit any student who uses this free tool.

THE TEST BEDS: THREE ENGINEERING DESIGN CHALLENGES

Three design challenges, each addressing a different scale of the built environment, will be used in middle and high school physics or engineering classes to provide the research data. Each challenge requires 5-7 hours to complete, sufficiently short for teachers to accommodate it in their lesson plans. These challenges have been tested and refined in a previous DR K-12 project. Teachers will decide which and how many of the challenges will be integrated into their courses. Including three different design challenges in the research will allow us to examine how findings depend on the type and context of design. Furthermore, the number of design challenges students solve will be used as a variable in our analysis to examine whether students who spend more time on solving different problems attain better learning outcomes. The three design challenges cover science concepts related to energy aligned with NGSS performance expectations MS-PS3-3/4 and HS-PS3-1/3/4. The supporting instructional materials are scaffolded using all of the ETS1 engineering core concepts and practices. For example, students are required to design a number of alternative solutions of their own, from which they select the best to be the final solution and justify their choices. They must use energy simulations to generate data for analysis, based on which they iteratively improve their designs. We will experiment if conformance analysis (Trčka, et al., 2010) can be used to determine how well students actually follow these rules of engineering practices. The three design challenges are outlined as follows:

- **Passive Solar House**. This challenge is connected to the concepts of power, energy, solar radiation, sun path, heat capacity, heat transfer, insulation, control, and renewable energy. Students use these concepts to design a passive solar house that meets thermal comfort and energy efficiency goals. They exploit energy-saving strategies, such as passive solar, shading, and thermal mass for reducing diurnal temperature variations. As a house is a complex system that has many design choices, they learn how to choose an effective solution using a tradeoff matrix that addresses all the criteria and constraints. For instance, they decide the optimal sizes of windows on each side of the house based on considering the solar heating through the glazing during the day and the heat losses during the night.
- **Zero-Energy Building**. This challenge engages students to design a commercial building that consumes zero net energy. To achieve this goal, students must learn to use multiple strategies: Energy must be harvested on-site through a combination of renewable energy-producing technologies like solar panels, wind turbines, or geothermal heat pumps; at the same time, the energy consumption must be reduced with sufficient insulation and weatherization, as well as efficient heating, cooling, and lighting. Students use the same set of science concepts as in the Passive Solar House project, but design a more complex building that includes the application of green energy technologies.
- **Solar Urban Planning**. This challenge requires students to design a cluster of buildings in a metropolitan area to ensure optimal access to solar energy. To make design decisions, students can display the sun's position and path at any given date, time, and location, generate a horizontal solar heat map of the planned area, compute incident solar radiation on any surface over any period, and examine ways to minimize obstruction of sunlight to existing buildings (which serve as design constraints). Students must consider the interplays among new constructions and existing buildings, as well as the effect of the shape of each individual building.

The problem and design space provided by the three design challenges is deep and wide. There are countless combinations of locations, orientations, shapes, materials, renewable energy solutions, and architectural features of buildings students can choose and test. All these design factors are linked to science concepts, creating an abundance of opportunities to learn and apply science.

Research Participants

Over the five project years, a total of more than 3,000 secondary students in two states will participate in this project (see the attached teacher letters). Each student will complete at least one design challenge selected by the teacher. The socioeconomically diverse schools are listed below:

School	Lead Teacher	# Students/year	Minority	Lunch Aid
Arlington HS (MA)	Larry Weathers	200	16%	10%
Framingham HS (MA)	Peter Erbland	70-80	27%	23%
Hammond District (IN)	Alicia Madeka	500	92%	83%
Lowell HS (MA)	Anthony Iarrapino	300-400	59%	58%

Ottoson MS (MA)	Larry Weathers	100	23%	11%
Plymouth North HS (MA)	Michael Bastoni	40-60	11%	25%

Table 1. At least 1,200 students from the above schools will be involved in this project each year in Years 3-5.

DATA SOURCES AND QUALITY CONTROL

A complex CAD process consists of numerous actions and events that occur sporadically, progressively, or iteratively within the problem space. Along with the properties of the designed artifacts that can be calculated dynamically by the CAD tool based on the underlying scientific laws, the types, timestamps, orders, frequencies, and durations of student actions accurately reflect the design process of each student. These process data can be collected as *time series*—sequences of data points chronicling the states of an ever-changing designer-design system. In this way, an intervention will leave a measurable trace to its full extent. Assessments can then be viewed as the analysis of a comprehensive set of time series, each representing an aspect of learning or performance over a period of time (Figure 1). To assess other variables in learning, the process data will be supplemented by data from the following instruments:

- **Pre/post-tests of science and engineering knowledge**: These instruments will measure students' understanding of science concepts and engineering principles before and after design projects. Items will be drawn from existing instruments such as the Heat and Energy Concept Inventory (Prince, Vigeant, & Nottis, 2012) and the Survey of Cognitive Dissonance in Engineering Design (Purzer, Hilpert, & Wertz, 2011). Pre/post-tests will be administered via Purdue Qualtrics, Web-based survey software provided through Purdue. If students solve multiple design challenges as required by their teachers, the post-tests will be administered after the completion of the last challenge.
- **Student surveys, interviews, expert evaluation, case studies, and classroom observations**. These will contextualize the pre/post-tests and process data and will be used to check the reliability of the time series logger, gauge the fidelity of the process data, and test the computer algorithms.

The quality of the process data will be controlled using the following strategies:

- **Minimize the "learning the tool" part**: As with any other tool, there will be a learning curve for Energy3D, however simple and intuitive its user interface may be. Our strategy is to begin the project by having students watch a five-minute tutorial video that introduces the basics of Energy3D and then give them 30 minutes to learn and explore it freely. Only after they start to work on a design challenge will the process be logged. Our previous pilot tests have suggested that the data from then on contained less random exploratory data not pertinent to solving the design challenge.
- **Collect data from individual students**. Sharing a computer among multiple students, whether or not they are working as a team, is problematic to this research because it would be difficult to distinguish individual actions and learning. In this project, students will work on separate computers. We expect that the opportunity to design individual products and the pride of ownership will create a need to show, share, and discuss (Papert, 1991). If a participating school does not have sufficient computers in a scheduled time slot, CC will provide supplements from its 120-laptops pool.
- **Pre-process the data**: Analyzing data that have not been screened for erroneous conditions can produce misleading results. To prevent this, we will run preliminary analysis to "clean" and organize the process data. For example, a process dataset showing long idle time indicates that the student was somewhat disengaged and should be considered as an outlier that requires further diagnostics.
- **Avoid intermittent Internet connections**: To ensure the integrity of the data, Energy3D will log data onto a USB flash drive provided to each student if no reliable Internet connection is available.

The Process Analytics to Decipher Big Data

In the following subsections, we will present the process analytics and explain how they will address our research questions: RQ1 (**patterns and relationships in engineering design processes**), RQ2 (**the effect of engineering design processes on science learning outcomes**), and RQ3 (**the effect of scientific inquiry processes on engineering design outcomes**).

Pattern Recognition for Design Behaviors Using Time Series Analysis

Process data often look stochastic (Figure 3). But buried in the noisy data are students' cognitive processes. Time series analysis, which is widely used in signal processing and pattern recognition (Hamilton, 1994; Wei, 2005), will be used to discover meaningful patterns of learner behaviors from seemingly random data. At the basic level, each time series provides descriptive statistics, such as central tendencies and dispersions of values or frequencies and durations of events, for the attribute it presents. The following is a list of patterns these analytics seeks to identify:

- **Design space exploration (RQ1)**: In general, a design comprises a number of elements (building blocks) added and revised through a number of actions that set or change their properties. The dimension of the design space, therefore, can be characterized as the number of action types × the number of element types × the number of element properties, which, for a typical CAD tool, is in the thousands. The subspace a student explored in a project can be measured using the statistics from three kinds of time series: 1) **Action time series**: The number of times each type of action was taken represents the level of activity in exploring the concept or skill corresponding to that action type. For instance, if the student never invoked the solar simulator, it is highly likely that solar design was never explored. 2) **Artifact time series**: The number of each type of element present in a design artifact represents the level of activity in exploring the concept or skill corresponding to that element type. For instance, the absence of a solar panel in a design indicates that photovoltaics was probably not considered. 3) **Property time series**: The range within which a numeric property was adjusted during a design process represents how far the designer pushed the limits in the direction of that property. For example, only testing a solar house design for the winter months indicates that the designer did not consider possible overheating in the summer. Note that the data contained in these three types of time series has often been manually collected through video analysis (Purzer, 2011), which is so labor intensive that sophisticated computer vision and image analysis software has been proposed to aid the coding process (Sanna, Lamberti, Paravati, & Demartini, 2012). But in this research, coding will be automatic.
- **Iterative design cycles (RQ1-3)**: The iterative cycle of design offers the greatest potential for applying science knowledge (National Research Council, 2011). The objective of this analysis is to identify and measure the driving and the damping forces for design iteration. For example, inquiry promotes iteration, whereas design fixation (Jansson & Smith, 1991) inhibits iteration (an itera-

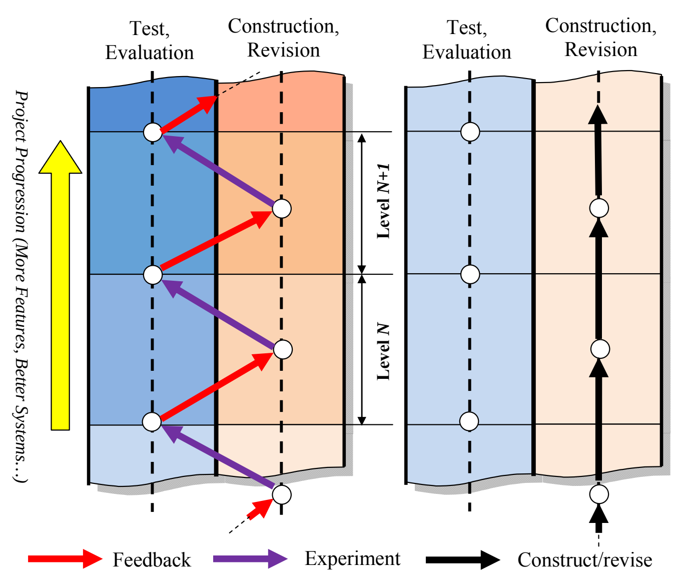


Figure 4. Left: An iterative cycle driven by experimentation to evaluate each design choice (an informed design activity). Right: A non-iterative behavior that does not involve any experimentation or evaluation step (a purely construction activity). Both behaviors have been observed in Energy3D logs and confirmed by classroom observations.

tion detector, therefore, may also serve as an inquiry or fixation detector). A complex design process may have multiple types of interwoven iterative cycles, each of which centers on one design aspect and requires its own detector. The following are two examples: 1) **System iteration**: For a designed system consisting of multiple interacting components, altering one may create a need to adjust others as well. After others are modified, the new configuration may invite a redesign of the original component and trigger a new round of revisions. This iterative behavior, which is related to systems thinking and coupled iterations (Adams, Turns, & Atman, 2003), can be easily detected by examining a time series that shows the component the designer worked on at any given time throughout a design process. The lack of system iteration in student data signals possible neglect or unawareness of the interactions within the system. 2) **Inquiry-driven iteration**: This detector will measure the extent to which iteration is driven by experiment-based inquiry. In a CAD tool such as Energy3D that provides science simulations for testing ideas, searching a design solution is an active process of inquiry through which students ask what-if questions and quickly find answers from the supporting simulations; the results of inquiry, in turn, become the catalysts for ideation in the next design step. This kind of iterative behavior can be detected by examining the alternating patterns of occurrence between analytical simulations (or virtual experiments) and construction or revision actions (Figure 4).

- **Temporal correlation (RQ1-3)**: Auto- and cross-correlation functions are two methods to measure temporal relationships that define the causality in learning. They also provide alternative methods for detecting iterative cycles. **Auto-correlation analysis** can find repeating patterns from noisy process data. **Cross-correlation analysis** can be used to examine if an intervention in one sub-process has resulted in changes in another and estimate how long it has taken for an intervention to regulate a design behavior (time lag). Of particular interest is whether cross-correlation analysis can capture the interplay between an experiment on a concept (e.g., solar energy) and a design process for a feature (e.g., windows), both of which are responsible for the improvement of product performance (e.g., energy efficiency). As shown in Figure 5, a time series that monitors construction actions and another that monitors test actions could show regularity similar to the alternating behavior illustrated in Figure 4.

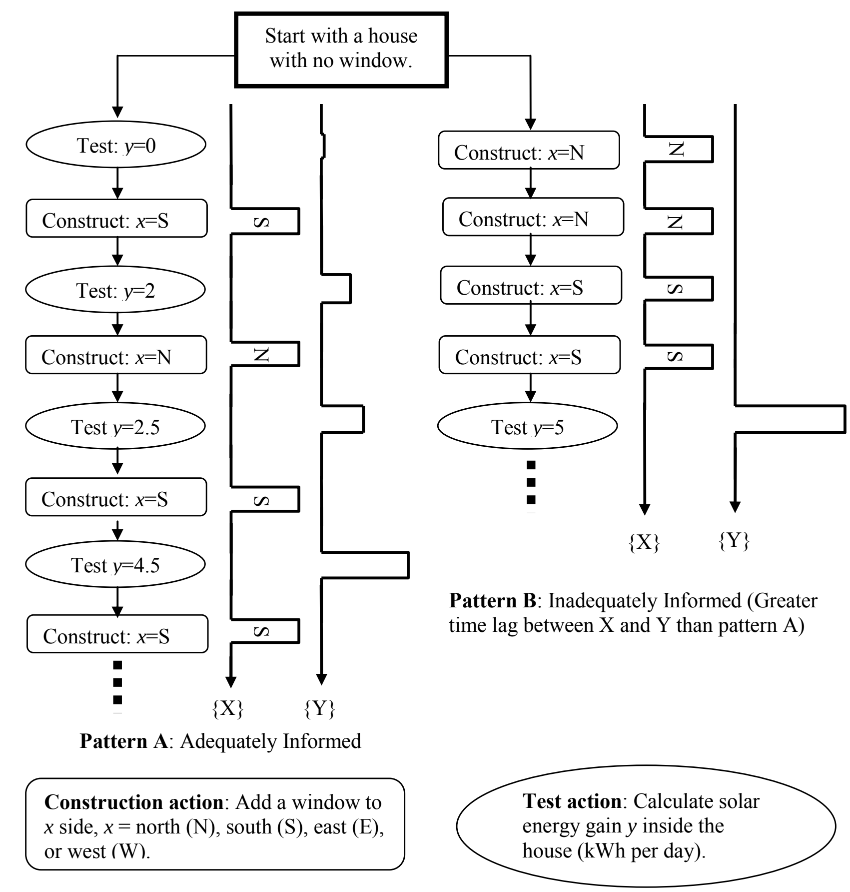


Figure 5. Two design scenarios of adding windows to gain solar energy. The cross-correlation function detects a greater time lag between construction and test steps in scenario B than in A, indicating that the designer in B would likely be less informed.

- **Clustering (RQ1)**: Cluster analysis classifies objects in such a way that objects in the same group are more similar to each other than to those in other groups. This project will use clustering to sort student data by gender, age, and pre/post-test scores. The objective is to discover relationships between learning patterns and those factors. Our algorithms will be based on the clustering of two types of data: 1) **The properties of a variable**. The distribution of the properties of any variable logged by the CAD tool as a function of a student factor will show whether there is any degree of clustering in the domain of that factor. For example, we can study if there is any gender difference in terms of the percentage of time students spend on simulation or reflection tasks. 2) **The shape of a time series**. Similarity measure between two time series (Esling & Agon, 2012) can be applied to behavior clustering and conformance checking (Trčka, et al., 2010). For example, this technique can compute if two design processes were similarly iterative, convergent, or divergent.

Association Rule Mining between Pre/Post-Test Data and Process Data

In the combined itemset of pre/post-tests and process data, the pre-test items are *antecedents* for the process data and the post-test items are the *consequent* of the process data (Figure 1). The association rule mining (ARM) method (García, et al., 2010; Merceron & Yacef, 2008) will address two relationships:

- **The effect of prior knowledge on design behaviors (RQ1)**: This can be measured using the *confidence* of a rule that quantifies the relationship between the pre-test score of item X (antecedent) and pattern Y (consequent) in the process data: $\text{conf}(X \Rightarrow Y) = \text{supp}(X \cup Y)/\text{supp}(X)$, where supp(X) is the *support* of item X. For example, if X is a test item about the concept of thermal conduction and Y is the number of the events of adjusting the insulation values of the walls, this value describes how many among the students who pass the pre-test of the science concept actually apply that knowledge in actions. The *lift* value of this rule, $\text{lift}(X \Rightarrow Y) = \text{supp}(X \cup Y)/[\text{supp}(X)*\text{supp}(Y)]$, measures the interplay between students' science knowledge and their design behaviors. A lift value greater than one indicates that their science knowledge has a positive effect on their design behaviors. A lift value smaller than one indicates that their science knowledge has a negative effect on their design behaviors (which is improbable, of course, and hence can be used as a test of the algorithm). A lift value near one means that their science knowledge has almost no effect on their design behaviors.
- **The effect of design behaviors on science and engineering learning outcomes (RQ1-2)**: This can be measured using the confidence of a rule that quantifies the relationship between the occurrence of a process pattern Y (antecedent) and the pre/post-test gain on an item Z (consequent): $\text{conf}(Y \Rightarrow Z) = \text{supp}(Y \cup Z)/\text{supp}(Y)$. For example, if Y is the number of times the solar simulator is turned on in the design process and Z is the understanding of the solar path (e.g., the sun is high in the summer and low in the winter), this value describes how likely designing solar features of a building with the aid of a solar simulator contributes to the acquisition of the science concept. Similarly, the *lift* value of this rule, $\text{lift}(Y \Rightarrow Z) = \text{supp}(Y \cup Z)/[\text{supp}(Y)*\text{supp}(Z)]$, measures the interplay between students' design behaviors and their science learning.

The Apriori algorithm will be used to identify the frequent itemsets from the pre/post-tests and process data to determine all the association rules. In order to test this ARM method in the calibration study, we will deliberately include in the pre/post-tests a few items that are not related to the design challenges. If the ARM method is accurate, the lift of any rule that associates these items with the process data should be close to one in most cases.

Combined Action-Note Analysis for Tracking Scientific Reasoning

While student performance can be observed from their actions, their design thinking is not observable. To probe into this "latent" process, the design challenges will require students to use the embedded notepad in Energy3D to diligently document their thought processes. Meanwhile, Energy3D will prompt students to take notes when it detects a critical event such as the completion of an energy simulation that needs to be followed by a summary or an explanation of the results. These **student-generated notes**, logged as string time series in parallel to the action time series (Figure 6), are useful in three ways: 1) they reveal the intent of the actions; 2) they contain student evaluation of the results of the previous actions; and 3) they indicate how reflective students might be in design processes (a student who spent more time on writing notes is likely to be more reflective). Evidence of scientific reasoning in design processes, which addresses both RQ2 and RQ3, can be found from these notes using the following methods:

- **Action-note alignment**: This will examine if a note taken before or after an action or a sequence of actions contains pertinent science keywords (the bolded words in Figure 6) and simulation data (the numbers in Figure 6). A typo-tolerant regular expression parser will be developed to find these textual patterns ("regular expression" is a computing term that specifies patterns in strings). A Hash table that maps each type of action to a group of regular expressions that cover a necessary set of science keywords and numeric formats will be used to calculate the percentage of actions associated with correct keywords and/or numeric evidence. A high rate indicates a high level of science in action.
- **Hidden Markov modeling**: As in the verbal protocol (Atman & Bursic, 1998) or document analysis (Dong, et al., 2004), a problem of detecting design thinking from student notes is that students may not articulate as frequently or thoroughly as needed. In the absence of a preceding or succeeding description for an action (or a group of actions), the underlying science ideas become "hidden"—we do not know for sure if the student understood or applied the science ideas or not. If such a case is counted as negative, the assessment would be an underestimation. To improve the accuracy of the process analytics, this project will explore the hidden Markov modeling (HMM), a class of computational methods for inferring non-observables from observables (Zucchini & MacDonald, 2009), for solving this problem. This is because a design process can be approximately modeled as a Markov process (Purzer & Fila, 2013)—what students will do next depends on the current states of their designs. For example, in a solar house design with Energy3D, where to add a new window depends on how many windows the house has and where they are now; what should be modified depends on the current energy simulation results. Importantly, our analytics will support the HMM prediction of individual students. For each student, the Baum-Welch algorithm will be used to determine the transition probability matrix and the observation probability matrix for the HMM method, a process known as "learning," based on his/her previous actions and notes. A strategy to ensure that each student has a history of notes sufficient for the Baum-Welch parameterization is to have the teacher reiterate the requirement that students must frequently take notes to explain or justify their design actions at least at the beginning of solving a design challenge. Using the Viterbi algorithm, such a trained hidden Markov model can then be used to determine the probability of "knowing or applying a concept" for actions that were not described (this mechanism is analogous to a speech recognition algorithm that can adapt to an accent after the user "talks" to it for a while). The feasibility of this approach is supported by the notable success of Bayesian Knowledge Tracing (Corbett & Anderson, 1995; Yudelson, Koedinger, & Gordon, 2013), a simple form of HMM for educational data mining

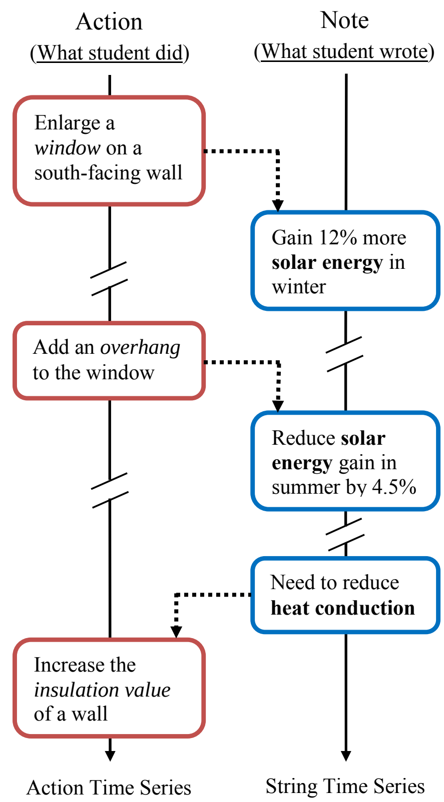


Figure 6. Probing students' scientific reasoning based on combined action-note analysis. In this hypothetical scenario, the occurrences of the science keywords in student notes related to the actions taken provide a measure of understanding and applying science concepts during design. If a note for describing an action is missing, the hidden Markov modeling method will be used to determine the probability of student understanding based on past actions and notes.

and intelligent tutor systems that Advisory Board member Baker has spearheaded (Baker, Corbett, & Aleven, 2008).

Calibration and Validation

The goal of calibration is to tune the instruments and test the analytics by comparing the results of the process analytics with the results from qualitative assessments based on expert evaluations of design processes, classroom observations of student activities, and post-project student interviews. The acquisition and analysis of data from these instruments will be based on a decade of research experience of this team on engineering design. Through careful calibration in Years 1-2, the process analytics will "learn" from the researchers how to mine the data more reliably and comprehensively. For instance, the calibration process will determine the itemsets for establishing a relationship between a science concept and a design pattern, the action-keyword table for mapping design actions to science knowledge, and the HMM parameters for designer modeling. New relationships that are not expected initially but emerge later in the research will be added to the mining list for the next round of data collection and analysis. In this way, the knowledge of the researchers will be incorporated into the process analytics, which will then be applied to the scale-up study in Years 3-5.

The goal of validation is to check the results from the process analytics against a subset of patterns from the Informed Design Teaching and Learning Matrix (Crismond & Adams, 2012). The following table lists this subset and the possible detectors from the process analytics:

Patterns	Beginning vs. Informed Designers	Detectors in the Process Analytics
F	Confounded vs. Valid Tests & Experiments	Count of simulated tests from action time series; temporal correlation of construction and testing
H	Haphazard or Linear vs. Managed & Iterative Designing	Iteration detectors
I	Tacit vs. Reflective Design Thinking	Combined action-note analysis

Table 2. A subset of patterns from the Matrix that will be used to validate the process analytics.

The samples of beginning and informed designers drawn from a class will be screened and determined by their pre-test scores on the Survey of Cognitive Dissonance in Engineering Design (Purzer, et al., 2011), as well as by interviews with the teacher and students to determine their prior engineering design experiences. If students solve multiple design challenges, their patterns in the first and last challenges will be compared as well to examine if they have become progressively more informed in the later phase. As there will be a distribution of student preparedness and progression, the detectors will likely show a range of values that capture different stages of design cognition development.

Prior Support

This proposal is based on the following three prior NSF projects of the three senior PIs:

1) Enhancing Engineering Education with Computational Thinking (DRL-0918449, $2,191,552, 10/2009-9/2013, PI: Xie). **Summary of results**: This DR K-12 project has developed the following products: a) two pieces of powerful engineering education software, Energy2D (Xie, 2012) and Energy3D, that have been used by tens of thousands of students worldwide, b) the Engineering Energy Efficiency Curriculum that challenges students to use science concepts to create energy-efficient scale model houses, c) "An Infrared Channel of Science"—a website that pioneers educational infrared imaging (Xie, 2011), and d) the initial version of process analytics that inspired the proposed project (Xie, et al., 2013). **Intellectual merit and broader impacts**: This project studies how computational tools, in particular CAD simulations, can be used to infuse science into engineering activities and thus improve student learning outcomes. The interactive, visual simulations developed in this project remove the barriers of learning due to difficult mathematics that often prevent K-12 students from understanding abstruse concepts. This project was recently featured by NSTA Reports (Shapiro, 2013). **Publications**: Five journal papers (including a cover and a featured article), one book chapter on 3D printing, and five conference presentations (including a keynote address at InfraMation—the world's largest conference on infrared imaging).

2) CAREER: A Study of How Engineering Students Approach Innovation (EEC-1150874, $466,681, 1/2012-12/2016, PI: Purzer). **Summary of results**: This ongoing project is studying students' innovation and creativity processes. The project uses advanced research methods such as the Markov chain analysis to quantify innovation processes (Purzer & Fila, 2013). **Intellectual merit and broader impacts**: The project has developed new metrics for assessing engineering design creativity. These metrics, measuring both design quality and novelty, have been used to evaluate designs by elementary students (Purzer, Myers, & Duncan-Wiles, 2012) as well as college students (Purzer & Fila, 2013). These methods aim to link student discourse and behaviors with student learning (Purzer, 2011). The work involves coding hours of video- and audio-recorded data to determine frequencies of certain behaviors and correlating the coded results to the learning outcomes. The critical products of this project are assessment tools and methods built on rigorous empirical data that come from qualitative and mixed-methods studies. **Publications**: One book chapter, four conference papers, and two invited presentations.

3) CAREER: Intentional serendipity, cognitive flexibility, and fluid identities: Cross-disciplinary ways of thinking, acting, and being in engineering (EEC-0748005, $495,830, 9/2008-8/2013, PI: Adams). **Summary of results**: a) completed data collection for a longitudinal study to investigate the nature and co-development of cross-disciplinary ways of thinking, acting, and being in engineering contexts in relation to disciplinary learning, b) designed and implemented collaborative activities to facilitate a scholarship of cross-disciplinary teaching and research, and c) piloted multiple ways to link education research and practice. **Intellectual merit and broader impacts**: The first phase of analysis resulted in a framework for characterizing the qualitatively different ways people experience cross-disciplinary practice in engineering that suggest an expanding awareness and engagement with "difference," complexity, and reasons for engaging in cross-disciplinary activities. The project has further substantiated a model of professional development and a method of educational research that could have broad implications in engineering education. Finally, the research approach has been expanded to include "multiple perspectives" and scholarship of integration approaches for advancing engineering education research. **Publications**: Four journal publications, three book chapters, seven conference papers, and four invited presentations.

Project Evaluation

This project will rely on a strong Advisory Board to evaluate the quality of the proposed research. In addition to frequent communication between the project team and the board members that will happen throughout the course of the project, three 1.5-day formal face-to-face meetings will be held at CC or Purdue. The first day of the meeting will focus on reporting and discussing the progress of the project. The remaining half day will focus on the project evaluation from an external perspective. The board members will review the proposal and determine how the project is meeting its goal and objectives along the scheduled timeline. Their evaluation reports will be included in annual reports to NSF.

Personnel

The Advisory Board

- **Dr. Alice Agogino** is Roscoe and Elizabeth Hughes Professor of Mechanical Engineering, University of California at Berkeley. Her research interests include document analysis, intelligent learning systems, data mining, CAD, interactive media, design theories, and gender equity.

- **Dr. Ryan Baker** is Julius and Rosa Sachs Distinguished Lecturer at Teachers College, Columbia University. He is President of the International Educational Data Mining Society. His research is at the intersection of educational data mining and human-computer interaction.
- **Dr. David Crismond** is Associate Professor of Science Education at the City College of New York. His research interests revolve around the issues of K-12 design cognition and pedagogy, and teacher professional development in science and pre-engineering.
- **Dr. Clive Dym** is Fletcher Jones Professor Emeritus of Engineering Design, Harvey Mudd College. The National Academy of Engineering's Gordon Prize Winner of 2012, he is well-known for his innovations in undergraduate engineering design education.
- **Dr. William Hutzel** is Professor of Mechanical Engineering Technology at Purdue University. His research focuses on learning, discovery, and engagement related to high-performance buildings. He has assisted with energy policy as a Congressional Fellow in Washington, D.C.
- **Dr. Tamara Sumner** is Associate Professor of Cognitive and Computer Science at the University of Colorado at Boulder. Her research interests include personalized learning, interactive learning environments, user-centered design, digital libraries, and intelligent information systems.
- **Dr. Steve Tanimoto** is Professor of Computer Science at the University of Washington. His research focuses on collaborative problem-solving environments and assessment technology including the use of pattern recognition methods in teaching of written language on tablets.
- **Larry Weathers** is K-12 Director of Science and Technology of Arlington Public Schools. A renowned educator, he has received a Presidential Citation from the White House for Excellence in Science Teaching and has been inducted into the Massachusetts Teaching Hall of Fame.

Senior Staff at the Concord Consortium

- **Dr. Charles Xie** will serve as the PI at CC. He is a computational scientist with 14 years of research and development experience in educational technology. He has authored ten journal papers related to STEM education research and created several widely used science and engineering simulation software tools. He is currently developing a unique, sophisticated package of process analytics for studying scientific inquiry and engineering design. Charles holds a Ph.D. in materials science and engineering from the University of Science and Technology, Beijing.
- **Dr. Saeid Nourian** will serve as the Co-PI at CC. He is the lead developer of Energy3D. Prior to joining CC, he has conducted cutting-edge research in 3D graphics, haptic interface, and other virtual reality technologies. Saeid holds a Ph.D. in computer science from the University of Ottawa.
- **Amy Pallant** will serve as a senior educational researcher. She has been developing curricula and contributing to research studies at CC for 13 years. She has served as the PI of multiple NSF projects. Amy has a Master's Degree in Science Education from Harvard University.
- **Dr. Helen Zhang** will serve as a senior educational researcher. Her research focuses on online science and engineering learning and assessment. Helen holds a Ph.D. in education in mathematics, science, and technology from the University of California, Berkeley.

Senior Staff at Purdue University

- **Dr. Şenay Purzer** will serve as the PI at Purdue. She is Assistant Professor in the School of Engineering Education and the Director of INSPIRE Assessment Research. She conducts research on assessing students' design, innovation, and engineering practices using methods such as discourse analysis and Markov chain modeling. She holds a Ph.D. in science education from University of Arizona.
- **Dr. Robin Adams** will serve as the Co-PI at Purdue. She is Associate Professor in the School of Engineering Education. Her research includes studies of engineering design knowing and learning, and cross-disciplinary thinking. She holds a Ph.D. in education from University of Washington. Her thesis focused on cognitive processes of iteration in engineering design.

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