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Evidence for the Effectiveness of a Grand Challenge-based Framework for Contextual Learning

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Student motivation – and associated educational outcomes – can be influenced by the degree to which course material connects to recognizable societal problems. The National Academy for Engineering has established the “Engineering Grand Challenges”, a set of 14 fundamental problems whose solutions will require integrated contributions from engineers, scientists, and policy-makers. The current work grafts the Engineering Grand Challenges (EGC) onto a pedagogical framework integrated into courses in several engineering disciplines, assessing whether this framework increased student motivation and, if so, what facets of learning benefit from this approach.

The EGC framework, as implemented here, follows a series of six stages that progress from statement of the problem, through exercises that teach a foundational concept using an EGC example, to reflection on the role of engineering in addressing the problem. The framework was implemented in three diverse courses: a computational methods course taken by all first-year engineering students, an upper-level signal-processing elective in electrical engineering, and a design course for upper-level students in environmental engineering. Instructors for each of these courses implemented the EGC framework in a manner appropriate for their course. For example, students in the signal processing course investigated the EGC of “Reverse-Engineering the Brain”, which included a lecture/discussion led by a neuroscientist who uses signal processing, followed by a project assignment that applied spectral analysis and filter design to publicly available data from a brain-computer interface contest. For all courses, baseline data were collected from the same classes taught by the same instructors in the previous year.

Results from the first year of implementation indicated significant benefits for the EGC framework, as well as differences in effectiveness across settings. Each student provided data that included self-reported ratings of ABET criteria and standard psychological measures of motivation, and those measures were included in structural equation models that predicted inter-student differences in grades. The EGC framework was associated with significantly higher self-reported class effectiveness, as indexed by ABET criteria. Furthermore, in advanced classes the EGC framework enhanced a key measure of student motivation (i.e., situational interest), which in turn was a positive predictor of ABET criteria. This effect was not present in the introductory class examined. No differences between EGC and baseline groups were found in other measures of self-reported motivation (e.g., perceived competence). Collectively, these results provide strong initial evidence that framing course activities around large-scale, societally relevant challenges can have salutary effects upon students’ motivation and skill development according to the ABET criteria. Ongoing work examines these effects across multiple semesters of the same courses, as well as across additional courses from throughout engineering curricula.

1. **Introduction**

The National Academy of Engineering (NAE) *Grand Challenges* (GC) call engineers to work within interdisciplinary research teams to solve problems of central societal importance. Key topics include reverse-engineering the brain, making solar energy economical, providing access to clean water, and enhancing virtual reality.[1] These challenges are complex, multiply determined, and fraught with social and personal complications. As such, solving them will require engineers who combine both technical training and other skills (e.g., ability to work in groups, communication, etc.).[2] Such complementary skills are often difficult to develop in the course of traditional engineering education, which often presents technical problems in abstract and stylized form without connection to real-world applications. Such education works for many engineers, but it risks missing those students who could be engaged by the opportunity to address problems of fundamental import.

Here, we describe a framework for integrating the NAE GC program into engineering education. We build upon prior examples of integration of real-world problems into engineering curricula: service learning (e.g., the EPICS program[3]), industry and non-profit internships, capstone design experiences, and cooperative learning internships. While such examples have been successful in many contexts, they are often seen as *additions* to curricula; that is, they are superimposed on a more traditional curriculum and courses. Our framework seeks to *integrate* theory and application so that real-world problem solving is embedded within courses to guide the learning of fundamental concepts and to increase student motivation. This framework holds promise for overcoming some recognized challenges of incorporating applications into engineering courses through psychological principles drawn from contextual learning theory. Its six stages progressively guide students from exploration of larger societal and technical contexts, through consideration of specific applications in engineering and related technical content, and back to the grand challenge and the potential role for engineering in improving our world. We describe how this framework was incorporated into several engineering courses taken by students in different majors and at different undergraduate levels, and we present assessment data from the first rounds of such courses that indicate the potential effectiveness of this framework for improving engineering education.

2. **Framework Description**

Our framework developed out of the recognition that integrating real-world problems into a curriculum can be extraordinarily difficult. To do so effectively introduces a tension between depth and breadth. Traditional approaches involve relatively narrow, discipline-specific problems, for example using auditory processing to motivate filter design (e.g., removing noise from a recording to improve the intelligibility of speech or the clarity of a musical recording). Such problems allow instructors to go into considerable depth within a single topic, but the broad implications of the approach may remain unappreciated by students. Conversely, using very broad, high-level problems to illustrate a concept can increase real-world relevance and spark students' recognition of how that concept can be applied in other contexts. Yet, instructors may find it very daunting even to teach diverse and interdisciplinary material, much less to incorporate such material into a hands-on project for their students.

Our *Engineering Grand Challenge*-based framework (or, EGC framework) incorporates broad, multi-disciplinary problems from NAE GC into diverse courses within undergraduate engineering curricula. It seeks to develop a generalized method that is appropriate for engineering students at different educational levels and in different majors. It comprises six stages completed in a particular order. In its first stages, students move from a broad consideration of the overarching problem to a discipline-specific perspective (Stages 1-3). Students then learn specific technical skills or content and apply what they learn to a real-world problem inspired by one of the GCs (Stages 4-5). Upon completing their technical work, they reflect on the skills they have gained and how those skills could be relevant for other aspects of the GC (Stage 6). We describe each stage in more detail in the following paragraphs.

Stage 1: Multi-Disciplinary Overview. Each GC project begins with an overview of one of the GC themes. Depending on the class needs and the availability of other resources, this overview could take different forms, such as a presentation from a technical expert in the field; a panel discussion among scientists, engineers, and policy-makers; general-interest reading assignments; an interactive on-line activity; or in-class discussions or debates about the topic. Regardless of the format, the key goals of this stage are to provide a general context in which the later discipline-specific skills can be grounded, to engage the students in thinking about the GC from perspectives both within engineering and across other disciplines, and to motivate the students' curiosity through examples drawn from real-world practice.

Stage 2: Definition/Problem Restatement. Students next independently evaluate the GC by reflecting on the multi-disciplinary overview and by re-defining the GC in their own words. This step encourages the students to think of themselves as active problem-solvers; i.e., they are not simply passive recipients of knowledge, but have the responsibility for seeking out skills that could help them solve this problem. They also consider the complexity of the GC to better understand what makes it a difficult but not intractable problem. This stage links the overarching GC to the discipline-specific projects they will complete thereafter (Stage 5: Application). While the exact instantiation of this stage varies across courses, it presents a good opportunity for students to develop communication skills (e.g., by writing a reflection paper) that are not typically expressed within engineering courses. Material generated in such assignments can establish a baseline for subsequent assessment activities (e.g., comparing descriptions of the GC from this stage to those generated at the end of the project).

Stage 3: Relation of the Grand Challenge to Engineering. In the next stage, students evaluate the question: What makes this a challenge for *engineering*? This requires them to reflect on the core features of engineering problems (e.g., optimization) and how engineers approach complex problems. By considering the specifically *engineering* aspects of this problem, the students make a very complex problem seem more manageable. This stage can be completed via in-class discussions or active-learning exercises, a writing assignment (potentially combined with Stage 2), or some other exercises as appropriate for the specific course.

Stage 4: Content, Tools, and Techniques**.** Next, instructors present course-specific content; that is, the technical material that would be part of the engineering course, regardless of the EGC framework. The method of instruction is left to the instructor's discretion – from a traditional lecture to in-class active learning. And, the instructor does not need to spend substantial time and energy (in this stage) relating the material to the GC. In practice, our instructors have taught the technical content using their standard approaches, simply pointing out a few conceptual connections to the GC during the class session.

Stage 5: Application of Course Content to the Challenge. Students then integrate the non-technical framework from Stages 1-3 and the technical material from Stage 4 within a problem-solving exercise. The exercises necessarily vary across courses, but they share common elements: hands-on involvement of the student (e.g., through a laboratory or in-class exercise), analysis of real-world data or simulation (e.g., electroencephalograms during a brain-computer interface), and reflection on ethical or practical issues raised by the data (e.g., whether the data indicate an acceptable level of performance, given cost constraints). Instructors are urged to connect their activities to local resources whenever possible (e.g., research laboratories or design firms). Successful applications will not only make the GC seem more tractable, but also reduce its scale to something that students can appreciate within a single exercise.

Stage 6: Analysis and Reflection. The final stage requires students to revisit the GC in light of their new skills and exploration of data, simulations, or other activities. Students should reflect – either through in-class discussions or individual assignments – on how the skills they developed could potentially address the GC and on what other skills/tools they (or other engineers) would need to make substantive progress. They should also repeat the "define the challenge" exercise from Stage 2 to provide an assessment of how their thinking has changed over the course of the exercise. This reflection also provides an opportunity to consider how engineers could contribute to teams to address the challenge, potentially expanding their perspective beyond their own discipline/major.

3. **Framework Implementation**

The EGC framework has been piloted in three courses – some taught several times – in the 2012-2013 and 2013-2014 academic years. These courses were at different levels (introductory required vs. advanced elective), were taught to students from different majors, and covered very different content. To give a sense of the breadth of coverage, we provide a brief overview of the implementation in the introductory course and then go into more depth about the details of implementation in an advanced elective course.

3.1 Computational Methods in Engineering

Computational Methods in Engineering (EGR 103L) is taken by all first-semester engineering students. It considers algorithms for the analysis of engineering problems and teaches computational methods (e.g., MATLAB) for implementing those algorithms. Thus, many of the GCs could be appropriate for this course. The GC theme *Make Solar Energy Economical* was chosen because numerous datasets exist that could be explored at an introductory level. Students initially summarized several non-engineering articles describing the challenge of solar energy, then spent one laboratory session in a non-technical discussion of how course content might be relevant for the GC. Note that other, earlier laboratory assignments taught data-management and analysis skills that were also indirectly relevant for the EGC project. That discussion fed into laboratory assignments in which they analyzed solar energy data from a collection site in North

Carolina . With that, they determined the necessary size of a modern solar panel to power a typical house's energy needs and evaluated whether such a panel would be cost-effective. Because the students were just beginning their engineering curricula, such exercises were necessarily more simplistic than those in other courses. However, introducing students to the GCs in their first semester does provide a potential benefit of setting the stage for other courses using the EGC framework.

3.2 Fundamentals of Digital Signal Processing

Fundamentals of Digital Signal Processing (ECE 381) is an advanced (junior/senior-level) elective for students majoring in electrical and/or biomedical engineering. It is typically taught as a small lecture course (e.g., 20-30 students). It introduces the theory and applications of digital signal processing, including topics such as sampling and reconstruction, discrete-time transforms (z-transform, discrete-time Fourier transform, and discrete Fourier transform), and the analysis and design of FIR and IIR filters. An accompanying laboratory engages students in software- and hardware-based exercises that illustrate many of the signal processing concepts discussed in the lectures (e.g., designing a system for classifying speech on the basis of vowel sounds). Because this course already has a structure in place for connecting lecture and laboratory material – and provides some flexibility in the examples that can be used – it was natural to incorporate the EGC framework.

In several semesters, a major component of the course has been a module based on the *Reverse-engineer the brain* GC. We chose this theme for two primary reasons. First, many of our students have interest in medical applications, generally, and in neuroscience, specifically. Second, there are many local experts within our academic community who conduct research at the intersection of engineering and neuroscience or who use signal-processing algorithms in the course of their research. We chose as our specific example that of "brain-computer interfaces" (BCIs), which often seek to use data collected from the human brain in the real-time control of some device or interface – of which perhaps the most visible and difficult challenge is to extract brain signals that allow paralyzed individuals to communicate verbally. We implemented the stages of the EGC framework as follows:

Stage 1 (Overview). Students were initially assigned three sorts of background material: (1) web and print material to familiarize them with the NAE Grand Challenges, generally[1], and the *Reverse-engineer the brain* challenge, specifically[4], (2) background readings and videos on brain-computer interfaces[5,6], and (3) the website of the guest expert for the module (Dr. Greg Appelbaum, a neuroscientist from the Duke Institute for Brain Sciences). We provided a set of relatively short and accessible articles/videos, recognizing that many of our students do not have substantial experience with material outside of their major. Students prepared three questions for Dr. Appelbaum, who gave a guest lecture on "Reverse Engineering the Brain: Primer for EEG and BCI approaches." This lecture provided an introduction to electroencephalography (EEG), including the hardware used for data collection, the algorithms used for data analysis, the uses of EEG data in neuroscience, and the applications of EEG for BCI. Because students were prepared for the lecture with three questions, they were able to readily and confidently contribute to a question and answer session.

Stage 2 (Restatement) and ***Stage 3 (Relation to Engineering).*** For the next stage, students read two articles on BCI from an engineering perspective.[7,8] Then, students restated the Grand Challenge of *Reverse-engineer the brain* in their own words. To add interest to this exercise, we framed this exercise as a memo to the Board of Directors of a company interested in BCI applications; the students described, from a signal processing perspective, one possible application of BCI and the opportunities and challenges therein. This framing approach was well-received by the students, in part because it forced them to step away from a purely academic approach to BCI and to consider real-world applications.

Stage 4 (Content, Tools, and Techniques). Supporting technical content was integrated throughout the semester. Most of the skills students needed to understand the signal processing within BCI applications were presented in lectures, homework, and laboratory assignments. To foreshadow the application (Stage 5) module – and to motivate students with an opportunity to apply what they were learning – some of the examples chosen throughout the semester were directly linked to EEG (e.g., a notch filter could be used to remove 60 Hz power-line noise from an EEG signal).

Stage 5 (Application). We provided students with publicly available EEG data collected at the Wadsworth Center at the New York State Department of Health as part of a BCI Competition.[9] The data were collected from a "virtual cursor" application, in which healthy participants unconsciously modulated naturally occurring brain waves to move a cursor to a target location on the screen; though simplified for this competition, this corresponds to one of the major approaches for BCI in paralyzed individuals. Students received a set of EEG training data (i.e., with known target locations) that they could use in developing their own algorithms. To do so effectively, they had to identify features of the data (e.g., energy in a frequency band associated with meaningful brain responses) that could discriminate target locations and then apply concepts learned in class (e.g., the Fourier Transform) to extract those features. They iteratively refined their algorithms on that training data and then generated predictions for a separate set of testing data (i.e., with unknown target locations) as part of a class contest.

Stage 6 (Analysis and Reflection). After the completion of the exercise, students reflected on the EGC module in a class discussion. This provided an opportunity for students to discuss their individualized progress (e.g., the arguments they raised in their Stage 3 memo, the choices they made in developing their Stage 5 algorithm). This generated a wide-ranging discussion that connected in-class activities to larger issues. In addition, several students expressed interest in pursuing BCI-related research in some form, through connections with Dr. Appelbaum or other researchers working in the general area.

4. **Impact on Student Motivation and Learning**

We have evaluated the impact of the EGC framework in the courses taught during the 2012-2013 academic year. Our overarching hypothesis is that exposure to real-world applications and exercises that encourage active problem solving will increase both student motivation and pedagogical effectiveness.[10-13] This idea – that learning is most effective when students can carry out activities and solve problems in ways that reflect the real-world nature of such tasks[14] – is based on theory and research on contextual learning in cognitive psychology and neuroscience.[14-17]

4.1. Assessment Strategy

We adopted the following assessment strategy:

Student Motivation. To examine how the EGC framework influences student motivation and subsequent academic achievement, we assess students' perceived competence in and interest/value for engineering. Perceived competence was measured using the 5-item self-efficacy scale from the Patterns of Adaptive Learning Survey (PALS).[18] A sample item includes 'I'm certain I can master the skills taught in my engineering courses.' Personal interest was assessed using an 8-item scale developed by Linnenbrink-Garcia and colleagues.[19] Sample items include 'Engineering is exciting to me' (enjoyment) and 'Engineering is practical for me to know' (value). Finally, situational interest was assessed with three subscales of four items each using a scale developed by Linnenbrink-Garcia and colleagues: catch ('The professor does things that grab my attention'), hold-feeling ('What we are learning in this class is fascinating to me'), and hold-value ('What we are learning in this class can be applied to real life').[19] All scales were highly reliable, with cronbach's alphas above 0.80.

Student Learning. To investigate effects upon student understanding of course material, we plan to take advantage of a comprehensive assessment approach implemented throughout the engineering curricula at Duke University. In Fall 2007, learning objectives and measurable outcomes were defined for all engineering courses; these allow quantification of student performance in terms of their proficiency on all assignments, not just in terms of final course grades. Moreover, because performance has been calculated for a subset of all students in every course since 2007, we have a meaningful baseline for comparing results in the EGC courses. These data provide an opportunity for future analyses.

Program Outcomes. We also predict that use of the EGC framework will have salutary consequences on non-technical areas of personal development that are now seen as important for training well-rounded engineers. For example, embedding technical material in the EGC framework may increase students' awareness of the global and societal implications of engineering, understanding of contemporary issues, and the importance of life-long learning; these correspond to ABET criteria h, i, and j. In end-of-semester surveys, we ask students to rate the degree to which the course increased their ability to achieve the ABET a-k objectives, and then multiple regression analysis evaluates whether there are improvements in selected criteria. We have used a similar approach in prior research evaluating the redesign of an introductory Electrical and Computer Engineering course.[20] In future analyses, we will be able to compare student responses for the EGC courses to baseline data from more than 6 years of student surveys.

Baseline data. In addition to the historical baseline data described above, we collected survey measures from 387 students enrolled in engineering courses (including two of our EGC courses) during the 2011-2012 academic year. We used hierarchical multiple regression analysis to examine motivational variables (perceived competence, personal interest, situational interest, and epistemic beliefs) as predictors of learning outcomes, after controlling for other factors suspected to influence learning outcomes (e.g., prior ability and gender). The results were consistent with other published studies: Perceived competence was positively associated with grades and achievement of course learning objectives; personal interest was positively associated with course learning objectives and ABET outcomes; situational interest (catch, hold-feeling, and hold-value) was positively related to grades, ABET outcomes, and learning objectives. Taken together, these findings highlight the importance of supporting motivational beliefs to support learning and engagement in engineering classes.

4.2. Results and Discussion

We used structural equation modeling to understand how the EGC framework supported two factors (*personal interest* in the overall course material and *situational interest* in the specific EGC content) to predict ABET criteria and course grades. Note that because initial testing did not find differential effects on the different ABET criteria, we collapsed across them in our modeling. Essentially, this approach posits that a manipulation like the EGC framework would have indirect effects on desired outcome variables (ABET criteria and grades) through its effects on student motivation. As a treatment variable, we compared data from the EGC courses to data from the baseline period described in Section 4.1. And, we measured *personal interest*, both at the outset and end of the course, as a way of partially controlling for overall differences in student interest and thus modeling changes in personal interest during the course.

Regarding student motivation, we found distinct results for students in introductory and advanced courses. For students in introductory courses, we found no significant effects of the EGC framework on psychological measures of motivation. Instead, the students' relative *personal interest* in engineering at the beginning of the course as well as their situational interest (interest in material taught in the course) were both significant predictors of their *personal interest* later in the course, and that second measure of personal interest was itself a significant predictor of grades and ABET criteria.

But, for students in advanced courses, our structural equation modeling revealed several striking effects. The EGC framework was associated with significant increases in *situational interest* (but had no significant direct effects on *personal interest*). The pathways linking *situational interest* to ABET scores and grades were not entirely stable, given our smaller sample of advanced students, but there was some evidence that higher situational interest was associated with small changes in personal interest over time and higher ABET scores.

These results provide initial evidence that our EGC framework improves student-reports of ABET criteria through its effects on student motivation. A strength of our assessment approach is the inclusion of well-controlled baseline data about the effects of student motivation on those same outcomes; those baseline data were drawn from similar courses, instructors, and students, strengthening the conclusions we can draw from our analyses. Our conclusions must be tempered, however, by our failure to identify a significant overall increase in student motivation based on the EGC framework. As alluded to previously, the most parsimonious explanation for our results is that the EGC framework (as implemented here) increases the motivation for a subset of students, but has little effect on motivation for other students. Examination of data from the current year will increase our sample size, potentially revealing effects missed in the first year's data. Our ongoing work investigates whether we can identify the specific types of students (e.g., based on personality variables) who would most benefit from the EGC framework. Future work will extend these analyses to consider the effects of this intervention on student learning outcomes.

Based on our first experiences with the EGC framework, we have made some structural changes to how we are implementing it in courses. Our analyses (and informal feedback from students) strongly suggest that starting EGC projects earlier in the semester would increase its impact for students; e.g., by encouraging them to think about real-world applications for other course material, or by providing them with a broader set of tools for analyzing data. Beginning in Fall 2013, we revised our courses so that references to the GCs are embedded throughout the semester, along the lines of the example in Section 4.2.

5. **Conclusions**

We have now implemented the EGC framework in several engineering courses targeted at different student levels and majors. Data collected in advance of the EGC intervention provide a reliable baseline for comparison to subsequent results. We used structural equation modeling to evaluate whether the EGC framework influenced desired outcomes through effects on student motivation; we found such a result for upper-level courses, but not for lower-level courses. We interpret our results to indicate that the EGC framework increases motivation for a subset of engineering students, and we are now exploring ways of engaging a larger set of students and of identifying those students who would be most likely to benefit from this framework.

Future plans include the implementation of the framework in two additional courses in the Spring 2014 semester (in Civil and Environmental Engineering), one a required upper-level course, the other an interdisciplinary senior design course. The framework will also continue to be implemented in *Computational Methods in Engineering* and *Fundamentals of Digital Signal Processing* again in the Fall 2014 semester, with additional themes and modifications in implementation based on our findings from earlier offerings.

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