

Honest Expert Solutions Towards Cognitive Apprenticeship

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Introduction

The use of provided examples as a method for teaching students engineering problem solving processes is used in many engineering classrooms. By using this method, instructors are attempting to model expert problem solving processes for their students in order to help them develop the cognitive and metacognitive strategies necessary to solve many of the problems they will encounter when they enter industry or pursue further academic study. This work focuses on the development of an intervention meant to provide students with access to the honest problem solving processes of experts when solving statics problems. Using cognitive apprenticeship as a theoretical framework, we seek to look at the impact that exposure to honest problem solving strategies has on novice problem solving skills.

Literature Review and Theoretical Framework

Problem Solving in Statics

The ability to problem solve is a critical skill that is required of undergraduate engineering students in the United States. The need for this skill is reflected in ABET Criterion 3. (e) that states that students must be able to "identify, formulate, and solve engineering problems"¹. While many courses in different engineering curriculums have a focus on problem solving, statics is typically the first course in many students' undergraduate engineering coursework that requires them to use an engineering problem solving process. Many researchers have spent significant resources investigating how students learn in statics and how to effectively teach problem solving in statics courses. For instance, Steif, Lobue, Kara, and Fay developed an intervention where students where engaging in talk about salient features of the statics problem². Steif and team found that students that were engaged in body centered talk were better at representing unknown forces on free body diagrams than students that did not participate in the intervention. Litzinger et al. looked at the differences in cognitive and metacognitive strategies between weak and strong problem solvers in statics ³. Litzinger and team found that the weak and some of the strong problem solvers relied heavily on memory when attempting to represent forces on a free body diagram. They also found that students who engaged more heavily in selfexplanation tended to be stronger problem solvers.

In all of these studies, researchers looked to discover differences between strong and weak problem solvers or to develop interventions in order to strengthen the problem solving skills of engineering students in statics courses. While these studies have looked at the impacts of cognitive strategies or certain pedagogical interventions on problem solving skills, few have looked at the impact of an intervention focused on exposing students to modeling of an expert problem solving process on problem solving skills. In the next section, we will discuss why modeling of problem solving processes is a key component to helping students learn problem solving skills. Specifically, we will highlight the need for exposing students to true expert problem solving processes that include a capture of the failures and successes that lead to a solved problem.

Cognitive Apprenticeship

In their work on how experts and novices categorize problems, Chi, Feltovich, and Glaser found that there is a fundamental difference in how expert and novice problem solvers sort problems into categories ⁴. They found that novices looked at physical features and given information from the problem statement to classify problems into categories. Experts used knowledge of the states and conditions of the problem to categorize problems. This study identified that different cognitive strategies were used by experts and novices in the beginning task of sorting problems into categories.

Being exposed to the problem solving processes of expert problem solvers is a critical learning activity for novice problem solvers. Brown, Collins and Newman describe a process called cognitive apprenticeship where novice problem solvers learn the necessary integration of cognitive strategies used by expert problem solvers through an apprenticeship process⁵. In a traditional apprenticeship model, a novice is teamed up with an expert to learn a trade through close interaction with the expert. The tasks and strategies used by the expert are observed by the novice in order to learn techniques and skills. In cognitive apprenticeship, a similar approach is taken where the problem solving process of an expert is made easily observable to a novice for the purpose of exposing the novice to proper problem solving procedures and thought processes.

There are four main components to designing curriculum and environments based on the cognitive apprenticeship model: content, method, sequencing, and sociology. The area of content focuses on the types of knowledge that one must hold in a content area to be considered an expert. The method category refers to the ways that are used to promote the development of expertise. Sequencing refers to the order in which learning activities should be presented to develop expertise. Finally, sociology refers to the social context of learning environments that promote development of expertise. One critical component of cognitive apprenticeship is the idea of making the thinking strategies of experts visible to novices. Through the use of modeling techniques, an expert should make visible the different types of content knowledge used to solve problems ⁵. Specifically, Brown et al., state that the cognitive and metacognitive strategies of experts be highlighted to novices ⁵.

In an effort to teach problem solving to students in mathematics, Schoenfeld used a model similar to cognitive apprenticeship to show the cognitive and metacognitive strategies of an

expert to his novice students ^{6,7}. Instead of showing a clean version of the problem solving process, Schoenfeld took a more honest approach to displaying his problem solving process to his students. Schoenfeld challenged his students to bring in difficult mathematics problems to class. He would then solve the problems in class after seeing them for the first time. Many times, the problems would be so challenging that students would observe Schoenfeld have difficulty during the process. He would start, stop and restart many times until he came to the correct solution. Through using this method, Schoenfeld showed students a true picture of his cognitive and metacognitive processes while solving a problem.

We know that it is critical that we model problem solving processes for students in order for them to learn how to properly problem solve. We've seen examples of how honest versions of problem solving processes have been used in teaching expert processes. As we work to teach our students to become experts, we next need to consider how to engage our 21st century students using 21st century technology.

Technology and Cognitive Apprenticeship

The use of online learning tools and courseware is rapidly growing in the United States. In the Fall of 2008, 25.3% of total enrollment in postsecondary education institutions was attributed to online enrollment. In that same year, the annual growth rate of online enrollment was found to be 16.9% ⁸. A 2013 study by the same authors focused on the rise of Massively Online Open Courses, or MOOCs ⁹. This report showed that teachers and faculty are beginning to make the transition to teaching more through online methods. Though not all coursework will and should be transitioned to online learning, some vital components of the learning process can be transitioned to online to either free up class time for more active learning activities or to provide students with additional resources to support their learning.

Some work has already been done to look at the impact of engaging in courseware with performance in the statics classroom. Steif and Dollar also looked at the usage patterns of courseware software of students in statics courses to determine that students' self-regulation of using courseware may be a predominant factor in learning gains in statics courses¹⁰. Moseley and Sexton investigated the impact of showing screencasts of problem solving processes to students on their conceptual understanding in statics¹¹. They found that students appreciate the availability of extra resources that can help them develop their problem solving skills through homework assignments and exams.

The purpose of this study is to use the cognitive apprenticeship model by Brown et al. to develop a screencasting tool for students in a statics course to use to further develop their problem solving skills⁵. This tool will focus on showing students honest problem solving processes that experts use (mistakes, missteps, etc.) to solve statics problems. The next section discusses the

research question for the study, the development of the screencasting tool as well as the methods for the research study.

Research Question

The research question for this study is:

What is the impact of viewing an honest expert problem solving process on the problem solving processes of engineering students solving statics problems?

In order to answer the primary research question, a series of sub-questions were developed. The analysis section is framed around the following subquestions:

- 1. Were "honest" and "warning" videos viewed similarly by students?
- 2. What type of students viewed the intervention videos?
- 3. What is the impact of rate of viewing on performance (measured by Exam Practice Problems (EPP) and a Statics Concept Inventory (SCI))?

Method

The basic process of creating screencasts for typical engineering analysis problems is described by Moseley ¹². This paper is an extension to an earlier study that looked at the impact of using screencast technology focused on displaying an expert problem process on the conceptual understanding of students in a statics course ^{11, 13}. The study has been extended to include a new element: Instead of the instructor selecting problems to use to develop the screencasts, a colleague familiar with the course content chose the problem and created the problem statement in PDF form, ready for annotation using an interactive display. While setting up the software, the instructor glimpsed at the problem statement to make sure it covered the intended topic, but did not solve the problem until the screen capture was started. In this way, the process of developing the screencasts is very similar to the method used by Schoenfeld in teaching cognitive processes to mathematics students ^{6, 7}.

The screencasts used in this study recorded the instructor's first attempt to solve the problem, *without knowledge of the correct final solution*. The instructor used a think aloud method as they wrote, describing out loud their thought processes on how they analyzed the problem for important features, formulated and then executed a plan of action, and checked for errors in analysis or calculations. Minor background noise reduction steps were taken during post-processing of some of the screencasts.

Two different methods of providing students with the expert problem solving processes through screencasting were used in this study. One treatment used the "as recorded" or "honest" screencast. This treatment presented the instructor's first attempt to solve the problem exactly as

it was recorded—no editing for content, no fixing mistakes after-the-fact, and no pop-up annotations. When the instructor did make a mistake, it was eventually noticed, corrected, and the analysis continued from the corrected mistake. The intent was to record the instructor's approach as if they had been solving the problem on a whiteboard in front of a class.

The other treatment used the "warning" screencast. This treatment presented the exact same analysis as the "honest" screencast with the addition of a short pop-up annotation warning the student that the instructor had just made a mistake in numerical calculation, algebraic manipulation, application of theory, or incorrect assumptions. The mistake was not typically edited out, only noted visually for a few seconds when it occurred. Twelve of the screencasts included such mistakes. If no mistakes were made during a screencast, the second treatment group received the same video as the first treatment group. In three instances where the mistake took a significant amount of time to correct, the flawed analysis was noted and then the screencast was skipped forward to where the mistake was corrected.

The subjects of this study were students enrolled in two sections of a one-quarter required 1st year Statics and Mechanics of Materials class at a small teaching focused college in the Midwest. Each section of the class received a different treatment. Of the 46 total students enrolled in the class, 30 participated in this study. Participants were 1st and 2nd year students and were primarily mechanical engineering majors.

Data collection for this study involved three primary parts. The first was through tracking student access of the screencasts through the course management software, Moodle. The screencasts were provided as a link on the main course page with individual links to each screencast, showing the topic covered. The screencasts were presented with the following description:

"Homework Help Videos-- Screencast videos of [instructor name] solving example problems that are similar to your HW assignments will be posted here. Watch these videos to improve your understanding of fundamental concepts, how to approach the problems, what proper documentation looks like, and how to identify mistakes."

A screencast was provided for most topics in the course, for a total of 23 screencasts. The screencasts were posted to the course Moodle site as the topic was covered in lecture. Students were reminded of the screencast availability occasionally throughout the quarter, but viewing of the screencasts was not required. Student access times and frequency were gathered for each of the screencasts after the course was completed.

Topic #	Screencast Topic	Notes
1	2D Vectors	
2	3D Vectors	
3	2D Particle Equilibrium	warning version exists
4	3D Particle Equilibrium	warning version exists
5	Normal Stress	warning version exists
6	Shear Stress	warning version exists
7	Stress on Inclined Planes	warning version exists
8	Stress and Strain	
9	Thermal Strain	
10	Axial Deformation	warning version exists and is 3 minutes shorter
11	Statically Indeterminate Problems	warning version exists
12	Factor of Safety	warning version exists
13	Moment About a Point	
14	Moment About an Axis	
15	Couples	
16	Centroids by Integration	
17	Centroids by Composite Bodies	warning version exists
		major topic of Exam Practice Problem 2
18	Distributed Load Equivalents	
19	FBDs of Rigid Bodies	
20	Equilibrium in 2D	
21	Equilibrium in 3D	warning version exists and is 2 minutes shorter
22	Friction	warning version exists
23	Frames & Machines	warning version exists and is 10 minutes shorter
		major topic of Exam Practice Problem 3

Table 1. List of screencast topics, noting when the warning treatment group received adifferent screencast, ordered as presented to students.

The second data collection part was through analyzing the students' analysis process on ungraded exam practice problems, given one or two lectures before the exam. The practice problem was developed at the same time as the exam itself with the goal of making the practice problem equivalent to a problem that would be seen on the exam. Students were told to approach the practice problem exactly as they would an exam problem so that they could self-identify if they should spend more time studying the topic covered by the practice problem. Students were given approximately ten minutes to complete the problem, their work was collected, and then the instructor's solution was shared and discussed.

After the course was completed, this ungraded assignment was assessed using a rubric that measures the performance of key problem-solving tasks in the subject—picking out key features of the problem, deciding on an analytical approach to use, correctly applying that approach, and checking the reasonableness of the result. The rubric focuses on procedural tasks, assigning a

score based on how well the student demonstrates their ability to follow the standard procedure. The rubric was developed by the instructor using a similar approach to Shadle, Brown, Towns, and Warner, and vetted by colleagues who regularly teach the same course¹⁴.



Figure 1. The Exam Practice Problem 2 (EPP2) handout is shown on the left and the evaluation rubric is shown on the right. The topic is finding a centroid by composite shapes.



Figure 2. The Exam Practice Problem 3 (EPP3) handout is shown on the left and the evaluation rubric is shown on the right. The topic is finding all forces exerted on a member of a multi-link frame. Because of the length of the problem, most students did not get far enough in their analysis to check their result, so the "check result" category was dropped for scoring.

The third data collection part was through pre-class and post-class concept inventories located at cihub.org. On the first day of class, students completed the Force Concept Inventory (FCI)¹⁵. During the last week of class, students completed the Concept Assessment Tool for Statics (CATS), referred to here as the Statics Concept Inventory or SCI¹⁶. The FCI results are intended

to allow comparison of how well individual students are prepared for the course by assessing their understanding of fundamental concepts related to the analysis of forces. The SCI results are intended to allow comparison of how well individual students have learned fundamental statics concepts after they have completed the course.

The data collected in this work are presented in Appendix A.

Analysis

In order to answer the main research question for this study, we first will address the subquestions that were developed.

Were "honest" and "warning" videos viewed similarly by students?

In order to determine the impact of both video treatments, we first must determine the usage rate of each treatment. To do this, we ran a two sample t-test assuming equal variance between the honest and warning groups. Treatment 1, the "warning" group, had a viewing average of 10.4 and a standard deviation of 15.5. Treatment 2, the "honest" group, had a viewing average of 13.6 and a standard deviation of 23.0. The two-sample two-tailed t-test assuming equal variances found p = 0.664. Students' usage of the screencast resource does not seem to be affected by the "honest" or "warning" differences. The data does not reject the null hypothesis that the two treatment groups' viewing frequencies were the same.



Figure 3. Box plots of screencast views shows no significant differences in the number of raw screencast views between the two treatment groups. A similar result holds for the non-repeat view data.

What type of students viewed the intervention videos?

Next, we looked at what types of students viewed the intervention videos during the quarter. To do this, we took the FCI score as an estimate for preparation for the class with regard to fundamental ideas of forces. The high-viewers (those with a raw view of 8 or more times) came from low, medium, and high ranges of FCI score. Conversely, low-viewers also came from a wide range of FCI scores. From this, we concluded that a wide range of students (more prepared vs. less prepared) used the intervention videos during the course.



Figure 4. Students with a wide range of incoming FCI score ended up being high-viewers of the screencasts (those with 8 or more views).

Looking at the data in a retrospective way, the high-viewers also seemed to end up with a wide range of SCI score at the end of the class.



Figure 5. High-viewers of the screencasts (those with 8 or more views) had a wide range of SCI scores upon completing the class.

What is the impact of rate of viewing on performance (SCI and EPP)?

To look at the impact of rate of viewing the intervention videos on performance in the course, we used regression analysis. Due to the potential impact of pre-existing knowledge on performance in the class, we also included the FCI score into each regression model. First, we can look at the impact of rate of viewing on performance on the EPP's. Table 2 presents the regression analysis of EPP2 score with the variables FCI score and number of video views.

Regression Statistics					
Multiple R	<mark>0.06</mark>				
R Square	<mark>0.00</mark>				
Adjusted R Square	-0.08				
Standard Error	0.97				
Observations	28.00				

 Table 2: Regression Analysis for Impact of FCI and Views on EPP2

	Coefficients	Standard Error	t Stat	P-value
Intercept	1.86	0.50	3.70	0.00
FCI	0.21	0.86	0.24	<mark>0.81</mark>
Views	0.00	0.01	-0.21	<mark>0.83</mark>

Table 3 presents the regression analysis of EPP3 score with the variables FCI score and number of video views.

Table 3: Regression Analysis for Impact of FCI and Views on EPP3

Regression Statistics				
Multiple R	0.22			
R Square	<mark>0.05</mark>			
Adjusted R Square	-0.02			
Standard Error	1.15			
Observations	29			

	Coefficients	Standard Error	t Stat	P-value
Intercept	1.81	0.58	3.11	0.00
FCI	1.03	1.01	1.03	<mark>0.31</mark>
Views	-0.01	0.01	-0.59	<mark>0.56</mark>

Both Tables 2 and 3 show little to no prediction power in the regression models (EPP2 $R^2 = 0.00$; EPP3 $R^2 = 0.05$). Thus we can conclude that the variables of FCI score and number of views provide little ability to predict a student's score on exam practice problems.

Next, we can look at impact of viewing on SCI score. Table 4 presents the regression analysis of SCI score with the variables FCI score and number of video views.

Regression Statistics				
Multiple R	0.65			
R Square	<mark>0.42</mark>			
Adjusted R Square	0.38			
Standard Error	0.14			
Observations	29			

Table 4: Regression Analysis for Impact of FCI and Views on SCI

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.14	0.07	1.98	0.06
FCI	0.52	0.12	4.35	<mark>0.00</mark>
Views	0.00	0.00	0.24	<mark>0.82</mark>

The regression analysis for SCI score shows that the variables FCI score and number of views can explain 42% of the variation in SCI score (SCI $R^2 = 0.42$). From this model, FCI score is a significant contributor to the model (FCI p = 0.00) while number of views was found not to be significant (Views p = 0.82).

The regression analyses for EPP scores and SCI score indicate that there was no significant relationship between how many times a student viewed the intervention videos and performance. Due to this result, there was no need to look at the difference between the honest and warning videos. While there could be many contributing factors to the results of this analysis, the most influential factor is likely the small sample size in the first round of data collection. Further rounds of data collection will occur in order to develop a more robust regression model.

Discussion

We now revisit the primary research question:

What is the impact of viewing an honest expert problem solving process on the problem solving processes of engineering students solving statics problems?

Based on the analysis of the data collected, viewing honest expert screencasts makes no measurable impact on demonstrated problem solving processes of students solving statics problems.

Students accessed the screencasts in equivalent numbers, regardless of the presence or absence of a warning about a mistake that was made by the expert. It seems that the time spent inserting a mistake warning in a screencast of an analytical solution might not be necessary.

The students who accessed the screencasts had a wide range of incoming conceptual preparation, as measured by the FCI, and also had a wide range of outgoing conceptual performance, as measured by the SCI. High-performing and low-performing students appear to be equally represented in the screencast viewing records.

No significant results were found to show that the treatments affected the outcomes measured—either through post-class SCI score or through exam practice problem scores.

However, there is something about the screencast resource that some students find appealing.

In this admittedly small study, honest expert screencasts are not shown to be a revolutionary idea that transforms the learning experience for an entire class. Yet, some students considered the screencasts as helpful—they watched them for many different topics and watched some of them multiple times. Informal verbal feedback throughout the quarter supported this feeling. What is still left to answer is what exactly students see as the benefit of these screencasts. Do they use the screencasts as an opportunity to practice along with the expert or do they sit back and watch what happens without working along? Do they focus on getting the correct final answer or do they try to practice the formal solution method that is being modeled? Does expert modeling of the identification and correction of errors help students in a homework or exam situation identify and correct their own errors? Finally, does showing that an expert does make mistakes improve their confidence in their ability to succeed in an engineering discipline?

Future plans for this research area include expansion of the treatment sample size and qualitative investigations to begin understanding why students choose to use the screencast videos.

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Appendix A

Participating students were randomly assigned an IDcode, with 100 designating treatment 1, "warning" videos, and 200 designating treatment 2, "honest" videos. Video views data is presented as both the raw number, counting the number of videos that were accessed, and as the non-repeat number, counting all accesses of the same video in succession within the same hour as a single access. Concept inventory results are presented as percentage scores. Exam practice problem scores are presented in total, out of a maximum score of 4. Data is sorted by the number of raw video views.

	Video views		Concept I	nventories	Exam Practice Problems	
IDcode	raw	non-repeat	FCI score	SCI score	EPP2 score	EPP3 score
154	55	51	40.0%	25.9%	2.5	4.0
108	22	18	83.3%	no data	no data	1.0
182	21	14	63.3%	55.6%	2.5	2.5
175	16	16	43.3%	44.4%	2.0	1.0
183	6	6	30.0%	37.0%	1.0	3.0
156	5	5	63.3%	59.3%	1.0	2.5
176	4	3	33.3%	40.7%	1.0	3.5
143	3	3	50.0%	37.0%	1.0	4.0
133	1	1	90.0%	51.9%	3.5	1.5
160	1	1	56.7%	44.4%	1.5	3.5
196	1	1	36.7%	11.1%	2.0	1.0
159	0	0	33.3%	48.1%	2.0	3.0
197	0	0	30.0%	37.0%	1.5	3.0

Table 5. Data for Treatment 1 group—"warning" videos, n = 13

Table 6. Data for Treatment 2 group—"honest" videos, n = 17

	Video views		Concept Inventories		Exam Practice Problems	
IDcode	raw	non-repeat	FCI score	SCI score	EPP2 score	EPP3 score
261	95	80	43.3%	33.3%	2.0	1.5
284	35	34	63.3%	37.0%	2.0	1.5
278	26	24	33.3%	40.7%	0.5	3.0
282	14	12	96.7%	63.0%	3.0	2.0
256	12	11	33.3%	51.9%	1.0	2.5
291	11	9	30.0%	25.9%	0.5	0.0
288	9	9	33.3%	14.8%	1.5	0.0
230	8	8	70.0%	51.9%	2.0	3.0
258	8	8	40.0%	29.6%	2.0	1.0
281	4	4	26.7%	14.8%	1.5	1.5

254	3	2	86.7%	37.0%	1.5	no data
219	2	2	50.0%	25.9%	2.0	2.5
269	2	1	83.3%	77.8%	4.0	2.5
277	2	2	66.7%	66.7%	3.0	3.5
225	1	1	70.0%	25.9%	2.5	1.5
231	0	0	93.3%	81.5%	4.0	4.0
237	0	0	43.3%	40.7%	1.5	2.5