Exploring Learner Engagement and Achievement in Large Undergraduate Engineering Mechanics Courses

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Undergraduate engineering mechanics courses often represent a significant challenge to the aspiring engineer because of the conceptually challenging course content and a misperceived status as final "roadblocks" before students enroll in specialized classes of a particular engineering discipline. Further, the mechanized nature of instructional and assessment methods in large lecture courses can decrease both satisfaction and engagement for students and faculty alike. It is thus no surprise that these fundamental mechanics courses are a major barrier for student persistence and success in engineering[1].

In considering means of improving teaching and learning in mechanics courses, delivery method is a common target. Halpern and Hakel[2] claim that lecture-style approaches can be "one of the worst arrangements for in-depth understanding" since "understanding is an *interpretive* process in which students must be active participants" (p. 40). Interventions such as increased hands-on demonstrations and flipped classrooms have shown positive outcomes.[3] Yet, historical practices, current class sizes, and financial demands on departments make it likely that large lectures will remain a primary delivery mode for these critical courses. This leads us to consider the nature of the course content itself in the context of students' active engagement. Though the written learning outcomes of a typical undergraduate mechanics course may be exclusively technical, the timing and nature of the course in the overall scheme of an engineering curriculum position it as a course that also requires students to develop proficiency in self-regulation and metacognition. Educational psychologist Paul Pintrich[4] describes these as "an active, constructive process whereby learners set goals for their learning and then attempt to monitor, regulate, and control their cognition, motivation, and behavior, guided and constrained by their goals and the contextual features in the environment" (p. 453). Specifically in Statics, successful students must learn to integrate knowledge and skills from several first-year engineering and mathematics courses, effectively manage time and study strategies, and develop an awareness of what concepts may require additional attention to excel on high-stakes achievement tests. Though student success in any course is a function of these interdisciplinary skills, because Statics represents such an early pivotal point in an engineering curriculum, student ability to self-regulate learning represents a critical area of further study.

This study seeks to inform and improve the challenging environment of large lecture-based courses in engineering mechanics through a better understanding of relationships between course engagement (e.g., time on task, methods of engagement) and achievement. In particular, this study reports on data from select Statics courses at a large, research intensive, land grant university in the Fall 2014 semester.

Metacognition in Engineering Education

Conceptualization of 'metacognition' within the engineering education literature has taken on multiple meanings,[5] including awareness of knowledge, thinking, and organizing cognitive resources.[6,7,8] For engineering students in particular, there are many benefits associated with enhanced metacognitive activity, in particular for their problem solving skills.[e.g.,5,9] Litzinger et al.[10] showed that stronger students engaged in metacognitive evaluation over twice as often as weaker students when they worked through problems in statics courses. In a similar research focus within statics courses, Steif et al.[11] found that metacognitive prompts asking students to monitor their steps in problem solving resulted in improved performance. Focusing at the conceptual level and using strategies to help students unpack the problem solving process and the structure of problems, other researchers working within chemical engineering[12], statics[13], and civil engineering[14] claim that metacognitive activities by their very nature help students become more self-aware and recognise gaps in their current knowledge. Prince and Felder's[15] review of inductive teaching methods argues that developing students' metacognition enables students to transfer knowledge between contexts.

Despite a shift toward application of education and learning sciences research within engineering education[16], there is still the need to improve understanding of how students can be taught to recognize their own learning behaviors so that they may engage in deep-level, integrative approaches to learning.[17] Such studies would focus on learning behaviors that occur at a higher level than the more specific metacognition studies of problem solving within engineering education. *Metalearning* refers to the specific aspect of individuals' awareness of their own approaches to learning more generally and their capacities to control it. Following the work of Biggs,[18] the development of metalearning has two stages: awareness of learning processes being used by oneself in some given context, and self-regulatory (internal) control over such processes in that same context. An intention to help students develop their metalearning capacity thus begins with the selection of a *learning context* in which to situate metalearning activities. A *mechanism* is then required that allows individual students' learning processes to become 'visible' in a conceptually meaningful way; that is, a mechanism that enables students to self-construct a representation of themselves as learners. The mechanism should explain to students (in language accessible to them) the meaning of contrasting strategies of learning and provide insights into where changes might be self-initiated. An Australian study by Meyer et al.[19] that focused on metalearning in undergraduate engineering demonstrated that using a reflective survey-based tool can indeed help students thinking about and recognize their learning strategies and provide empirically driven assistance that leads to changes in their learning behaviors.

In the current study, the learning context under investigation is undergraduate statics courses at a large research university. The mechanisms that we use to help students think about their learning processes are surveys throughout the semester before and after each exam. Similar in-class metacognition survey approaches have been used in undergraduate engineering to collect students' reports of confidence levels on different concepts before and after lectures.[20,21] Rather than investigating confidence in understanding for this particular paper, we focus more broadly on the time students choose to spend on a range of activities related to their courses. Reporting back to students how their time in aggregate varied across different activities and related to their academic performance in the course provides a mechanism to allow their learning processes become visible in a meaningful way.

Data and Methods

Two large (i.e., >100 students each) lecture-style Statics courses were studied during the Fall 2014 semester. Both sections had the same instructor, followed the same departmental course

schedule, and used a grading scheme where the overall homework grade and four high-stakes tests each account for 15% of the total grade and the final exam is weighted at 25%.
This study explored how often (hours/week) and through what methods (e.g., classroom attendance, office hours, independent problem solving, group problem solving) students self-report engaging with course content throughout the semester. These data were collected through a series of online surveys administered in the class periods before and after high-stakes achievement tests. Students could complete the survey during class meetings and also received a link to the survey so that it could be completed outside of class hours. To spur higher response via an incentive, students who participated were entered into a raffle for a gift card drawing at the end of the semester.

Prior to each exam, students were asked to respond to the following items that we investigate in this paper:

- Based on your overall average time spent engaging with Statics course content, please provide some clarification of how you spend time (hours per week) on each of the following activities related to engagement with Statics course content:
    - Classroom attendance
    - Reviewing the book text and worked out sample problems
    - Reviewing supplemental material in the WileyPlus online textbook system
    - Solving problems independently
    - Solving problems with peers
    - Visiting GTA or instructor office hours
    - One on one tutoring

Responses from the surveys were then paired with course achievement data (homework average, high-stakes tests 1-4, final exam, overall course grade). The response on the surveys corresponding to Test 1 included 157 students out of a total 340 students, and 77 students out of a total 310 for Test 2. The total number of students decreased throughout the course. We anticipate that this occurred because of students withdrawing from the course, survey fatigue, and dissatisfaction with overall course performance. Response rates on surveys corresponding top Tests 3 and 4 were low enough to warrant focusing only on Test 1 and 2 surveys for this analysis. Within the Test 1 and 2 window, the grade distribution of the sample is well aligned with the overall grade distribution, as shown in Table 1. For reference, Test 1 involves Vectors, Forces, Moments, and Equilibrium in 2-D while Test 2 covers the same topics in 3-D.

Table 1. Test score distribution for full class, students taking survey 1, and students taking survey 2

	Full Class		Took Survey 1		Took Survey 2	
	Test 1	Test 2	Test 1	Test 2	Test 1	Test 2
A	10.6%	11.7%	12.6%	8.5%	13.9%	14.3%
B	12.1%	13.7%	13.2%	17.6%	15.2%	15.6%
C	27.9%	30.8%	28.5%	34.5%	27.8%	36.4%
D	16.2%	14.6%	19.9%	18.3%	22.8%	20.8%
F	33.2%	29.2%	25.8%	21.1%	20.3%	13.0%
N	340	315	151	142	79	77

Our analyses explore how students spent their time engaging in the Statics course, how their time changed from Test 1 to Test 2, how their time in different activities related to performance on each test, and how their re-allocation of time among the different activities related to performance on Test 2. We report descriptive statistics to determine an overall understanding of time out of class, paired sample *t*-tests to understand how time changed from Test 1 to Test 2 (for those who responded to both surveys), analysis of variance (ANOVA) to relate time spent on different activities to performance on each test (on a letter grading scale), and multiple linear regression to relate time spent on different activities to performance on each test (on a number grading scale).

We acknowledge that our study has multiple limitations, and readers should take caution when interpreting results. First, our data include students' self-reports of time in different activities. Because we ask students to report on their recent time, this value is likely to be more accurate than if we asked them to report on time several weeks or months previously. To be more accurate, we could have recruited students to keep detailed journals or calendars of their time spent on Statics as a method of verifying their self-reports, but the current work is still in its exploratory stage. Second, our sample size decreased with each subsequent administration of the survey. Thus, the students who remained willing to continue engaging in the survey may have not been representative of the overall class in terms of their time spent outside of class. As shown in Table 1, the general patterns of test performance among survey takers compared to the overall course grade distribution were similar, but we have no way of knowing the distribution of time spent outside of class for the non-respondents. In the next semester's administration of the survey, we have reduced the number of items on each survey and will have an incentive raffle after each survey (instead of once at the end of the semester) to spur additional participation. Third, many students withdrew from the course following Test 1. This paper does not investigate how those students differed in their time allocation relative to those who completed Test 2. Additional analyses should focus on that population specifically.

Results and Discussion

Initial analysis focused on the time spent by the entire sample on Statics leading up to Test 1 and leading up to Test 2. The overall average time spent on Statics before Test 1 was 9.83 hours per week, with 2.59 hours outside of class for each 1 hour in class. Time spent on Statics before Test 2 was 12.57 hours per week, with 3.54 hours outside of class for each 1 hour in class. These results suggest that despite overall poor performance on both tests, prior to Test 2 students reported on average spending more time per week than what would be expected of a typical three credit hour course (i.e., 3 hours out of class for every 1 hour in class).

Table 2 displays a more detailed breakdown of how students engaged with course material, and Table 3 specifically investigates the change in quantity and manner of time spent from Test 1 to Test 2 (for those who participated in both surveys). Of the statistically significant changes from Time 1 to Time 2, students spent more time solving problems independently ($p<.01$), solving problems with peers ($p<.01$), visiting GTA or instructor office hours ($p<.05$), and reviewing the book text and worked problems ($p<.1$).

Table 2. Descriptive statistics of weekly time (in hours) spent on activities related to engagement with Statics course content.

	Survey 1 (n=157)		Survey 2 (n=79)	
	Mean	Std Dev	Mean	Std Dev
Classroom Attendance	2.74	.35	2.77	.44
Reviewing book text and worked problems	1.29	1.80	1.59	1.98
Reviewing supplemental material in online system	.67	1.08	.82	1.79
Solving problems independently	2.76	2.19	4.13	3.36
Solving problems with peers	1.72	1.82	2.34	2.90
Visiting GTA or instructor office hours	.61	1.33	.91	1.69
One on one tutoring	.04	.25	.01	.11

Table 3. Paired sample *t*-tests comparing students' time spent on activities related to engagement with Statics course content (includes student who took both surveys).

	Survey 1	Survey 2	*t*	*df*
Classroom Attendance	2.81 (.32)	2.77 (.44)	1.06	72
Reviewing book text and worked problems	1.25 (1.49)	1.60 (2.00)	-1.85*	71
Reviewing supplemental material in online material	.67 (1.06)	.80 (1.83)	-.60	72
Solving problems independently	3.08 (2.08)	4.32 (3.41)	-3.74***	72
Solving problems with peers	1.37 (1.53)	2.35 (2.97)	-3.73***	72
Visiting GTA or instructor office hours	.63 (1.33)	.97 (1.74)	-2.06**	71
One on one tutoring	.03 (.23)	.01 (.12)	.45	72

Note: *=p<.1, **=p<.05,***=p<.01. Standard Deviations appear in parentheses below means.

The increase in overall time spent on the course by the students seems like a reasonable overall response to a poor class average after Test 1, particularly given the frequency with which instructors commonly implore students to work harder. Yet, total time spent may not necessarily predict course achievement, particularly as courses become more conceptually difficult. To explore relationships between engagement and achievement, we followed two distinct methods. The first method categorized grades on Test 1 and Test 2 into the A-F scheme used for overall course grades, and an ANOVA determined whether significant changes were noted across grades on a specific variable (e.g. did classroom attendance prior to Test 1 vary significantly by grade grouping?) These results are shown in Table 4, and the only statistically significant variation found was for solving problems independently prior to Test 2. The second method was a regression analysis with grades as the dependent variable and different methods of spending time as independent variables; results are shown in Table 5. From this regression analysis, no activities predicted Test 1 scores significantly; similar to the ANOVA finding, solving problems independently was a statistically significant predictor of Test 2 score (R^2=0.25).

Table 4. Time spent on different activities by letter grade on each test. Shaded cells show significant differences in time across test letter grades, according to an analysis of variance (p<.001).

		A	**B**	**C**	**D**	**F**
Test 1	Classroom Attendance	2.68	2.80	2.74	2.77	2.69
	Reviewing book text and worked problems	1.22	1.18	1.34	1.18	1.43
	Reviewing supplemental material in online system	0.87	0.48	0.64	0.54	0.79
	Solving problems independently	3.32	2.93	2.40	2.85	2.83
	Solving problems with peers	1.55	1.70	1.71	1.45	2.09
	Visiting GTA or instructor office hours	0.43	0.38	0.60	0.93	0.65
	One on one tutoring	0.00	0.00	0.05	0.00	0.10
Test 2	Classroom Attendance	2.73	2.92	2.82	2.66	2.65
	Reviewing book text and worked problems	0.86	1.33	1.63	2.60	1.00
	Reviewing supplemental material in online system	0.32	0.67	1.09	1.22	0.00
	Solving problems independently	4.95	7.63	4.34	2.25	2.10
	Solving problems with peers	1.09	1.42	2.48	3.75	2.20
	Visiting GTA or instructor office hours	0.64	1.13	1.48	0.59	0.00
	One on one tutoring	0.00	0.00	0.00	0.06	0.00

Table 5. Regression analyses relating time spent on different activities to performance on each test. Note: the time items were unique and specific for each test.

Independent variables	**Coefficients**	
(taken before each test)	Test 1	Test 2
Classroom Attendance	-0.35	2.24
Reviewing book text and worked problems	-0.07	-1.00
Reviewing supplemental material in online material	-0.72	0.54
Solving problems independently	0.34	1.89***
Solving problems with peers	-0.35	-0.74
Visiting GTA or instructor office hours	-0.88	0.90
One on one tutoring	-6.98	1.71
R^2	0.02	0.25

Note: *=p<.1, **=p<.05,***=p<.01.

Results shown in Tables 4 and 5 represent distinct analyses in aggregate and do not specifically take into account that students may intentionally alter how they spend their time from Test 1 to Test 2. To explore this phenomenon, another regression analysis was performed using the change in time spent within each time category as a set of predictors for Test 2 performance (see Table 6). Increases in time spent solving problems independently, increases in visiting GTA or instructor office hours, and *decreases* in solving problems with peers were all statistically significant predictors of test 2 score (R^2=0.33).

Considered together, Tables 4, 5, and 6 lead to the first primary suggestion from this research: instructors should not simply encourage students to work harder (i.e., spend more time) and instead specify high impact pathways. That is, *students need to work both harder and smarter (spending more time in critical ways) to succeed*.

Table 6. Regression analyses relating change in time spent on different activities from test 1 to test 2 to performance on test 2.

Independent variables	**Coefficients**
(Time 2 minus Time 1 on each activity)	Test 2
Classroom Attendance	-4.70
Reviewing book text and worked problems	-0.43
Reviewing supplemental material in online material	0.65
Solving problems independently	2.70***
Solving problems with peers	-1.79**
Visiting GTA or instructor office hours	2.60**
One on one tutoring	4.86
R^2	0.33

Note: *=*p*<.1, **=*p*<.05,***=*p*<.01.

To better examine the data in light of this suggestion, we made the assumption that those students earning grades less than a B- are the population most in need of targeted advice about course engagement. Those poor performers on Test 1 also are most likely to consider following suggested changes because those who are already successful would not feel the need to change their strategy in the course. Thus, the previous analyses were repeated with only those students who earned less than a B- on Test 1 and are presented in Tables 7, 8, and 9.

Interpretation of data from this select sample is similar. In Table 7, those items that showed statistically significant differences in times from Survey 1 to Survey 2 remained the same as shown in Table 3 (though mean, standard deviation, and *p* values changed), The predictive model in Table 8 shows that visiting GTA or instructor office hours and solving problem independently are both statistically significant predictors of Test 2 score, with a notable increase in the amount of variance explained (R^2=0.34) when compared to Table 5 (solving problems independently and R^2=0.25). The regression analysis of Table 9 confirms the same relationships as with the full sample shown in Table 6: increases in time spent solving problems independently, increases in visiting GTA or instructor office hours, and decreases in solving problems with peers were all statistically significant predictors of test 2 score with a predictive model that explained more variance than seen in the full sample (R^2=0.37 versus R^2=0.34).

As a final note, careful consideration of the mean values for the various ways time was spent before Test 1 and Test 2 within each grade range reveals some interesting changes that undergird the predictive models. For example, students scoring below a B- on Test 1 all spent more time solving problems with their peers before Test 2, while their higher performing colleagues spent less time on average. Similarly, students earning an above a C- on Test 1 all spent more time solving problems independently, while the other groups spent less time.

Table 7. Paired sample *t*-tests comparing students' time spent on activities related to engagement with Statics course content (only includes students who earned less than a B- on Test 1 who took both surveys).

	Survey 1	Survey 2	*t*	*df*
Classroom Attendance	2.80 (.33)	2.74 (.49)	1.26	52
Reviewing book text and worked problems	1.20 (1.25)	1.64 (1.85)	-1.80*	51
Reviewing supplemental material in online material	.71 (1.11)	.90 (2.03)	-.64	52
Solving problems independently	2.82 (1.98)	3.90 (3.24)	-2.63**	52
Solving problems with peers	1.42 (1.47)	2.70 (3.18)	-3.82***	52
Visiting GTA or instructor office hours	.68 (1.48)	1.04 (1.95)	-1.68*	52
One on one tutoring	.04 (.28)	.02 (.14)	.44	52

Note: *=*p*<.1, **=*p*<.05,***=*p*<.01. Standard Deviations appear in parentheses below means.

Table 8. Regression analyses relating time spent on different activities to performance on each test. Note: the time items were different for each test.

Independent variables	**Coefficients**	
(taken before each test)	Test 1	Test 2
Classroom Attendance	0.83	-4.38
Reviewing book text and worked problems	0.29	0.47
Reviewing supplemental material in online material	-2.04	1.15
Solving problems independently	-1.04	2.35***
Solving problems with peers	-0.72	-0.96
Visiting GTA or instructor office hours	0.07	2.16**
One on one tutoring	0.52	-2.08
R^2	0.04	0.34

Note: *=*p*<.1, **=*p*<.05,***=*p*<.01.

Table 9. Regression analyses relating change in time spent on different activities from test 1 to test 2 to performance on test 2.

Independent variables	**Coefficients**
(Time 2 minus Time 1 on each activity)	Test 2
Classroom Attendance	-6.15
Reviewing book text and worked problems	0.36
Reviewing supplemental material in online material	0.56
Solving problems independently	2.28***
Solving problems with peers	-1.76**
Visiting GTA or instructor office hours	3.50***
One on one tutoring	1.70
R^2	0.37

Note: *=*p*<.1, **=*p*<.05,***=*p*<.01.

Conclusion

Undergraduate engineering mechanics courses often represent a significant challenge to aspiring engineers. Successful students must learn to integrate knowledge and skills from several first-year engineering and mathematics courses, effectively manage time and study strategies, and develop an awareness of what concepts may require additional attention to excel on high-stakes achievement tests. In this paper we investigated the different ways in which students spent time engaging in their Statics course material and related those activities to course performance. It was our early efforts at understanding how students go about managing their time in a traditionally challenging undergraduate engineering course.

Following an initial difficult exam, students in aggregate reported spending a substantial total amount of time outside of class (approximately 3.5 hours outside of class for each 1 hour spent in class). That time was allocated among activities such as working on problems independently, reworking problems from the textbook or examples from class, visiting office hours, and working on problems with peers. However, the effectiveness of those strategies on performance on the subsequent exam varied in both magnitude and direction. Spending more time solving problems independently most strongly related to higher exam performance, and spending more time working on problems with peers exhibited a negative relationship. Therefore, a major implication of our findings for faculty members to assist students on how to be more effective learners is to encourage students to work harder (in terms of time) but perhaps more importantly smarter (in terms of spending more time in specific ways). This recommendation is especially important in providing feedback on learning strategies to students who struggle on early exams. Our findings suggest that those students doubled down on poor strategies (i.e., working with peers), while their already more successful peers in the course enhanced strategies such as working independently on problems.

We are currently repeating this study in additional engineering mechanics courses in Spring 2015. Learning from initial data collection, we are seeking to address response rate limitations by reducing the length of the survey and changing our incentive strategy. In addition, we are bringing in results of this study and providing real-time feedback during the semester to students to help them make better decisions with respect to their time. Reporting back to students such results could provide a mechanism to allow students' learning processes to become visible in a meaningful way, which is the essence of an intervention to help develop students' metalearning capacities.

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