IJEMST

International Journal of Education in Mathematics, Science and Technology

ISSN: 2147-611X

International Journal of Education in Mathematics, Science and Technology (IJEMST)

www.ijemst.com

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To cite this article:

Grohs, J.R., Knight, D.B., Young, G.D., & Soledad, M.M. (2018). Exploring academic performance paths and student learning strategies in a large foundational engineering course. *International Journal of Education in Mathematics, Science and Technology (IJEMST), 6*(3), 241-253. DOI: 10.18404/ijemst.428175

International Journal of Education in Mathematics, Science and Technology

Volume 6, Number 3, 2018 DOI:10.18404/ijemst.428175

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Article Info

Article History

Received:
01 July 2017

Accepted:
08 January 2018

Keywords

Middle years
Statics
Metalearning
Large classes
Student strategies

Abstract

Situated in the second year of an engineering curriculum, undergraduate engineering mechanics courses represent a significant barrier to persistence in engineering. This study seeks to inform and improve these educational environments by examining academic performance paths over time in a course and explore how students in each path compare in the learning strategies they employ to engage with course content. Through online surveys, we gathered data on self-reported time spent engaging with course content before high-stakes testing in four large sections of a Statics course that were all taught by the same instructor. Cluster analysis identified groups exhibiting distinct performance paths, and one-way Welch's *F*-tests with post-hoc comparisons explored differences between these clusters based on time spent engaging with course content through specific learning strategies. Differences across performance clusters were found primarily in the ways in which students spent time rather than total time spent. Solving problems independently was a strategy employed significantly more often by the highest-performing cluster of students. In contrast, a group of unsuccessful students in the course spent comparably less time solving problems independently but comparably more time solving problems with peers. From these results, we suggest how leveraging these findings might impact educational practice and guide future research.

Introduction

Engineering mechanics courses frequently represent a significant challenge to students along the pathway to an undergraduate engineering degree and thus can be major barriers for student persistence and success in engineering (Lord & Chen, 2014). After completing general engineering coursework and university-level studies (e.g., mathematics, chemistry, physics), students are tasked with mastering more specific and technical engineering content, typically in the second year of study. Coupled with the challenging content, these classes tend to be characterized by large enrollments and are structured primarily in a lecture-based format because they are required across several engineering disciplines. Such educational environments are not always conducive for students to digest conceptually difficult course content and receive timely individualized feedback. For example, Halpern and Hakel (2003) 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). Although some programs have been successful with adjusting pedagogical approaches (e.g., introducing flipped classroom models) (Bishop & Verleger, 2013), the large lecture model still characterizes the structure of many programs and likely will continue to do so because of resource availability, organizational inertia, and swelling enrollments.

Within this early stage of their curriculum, students often find themselves at a crossroads of mastering technical content while simultaneously navigating how to be an effective learner in college (i.e., the development of self-regulation and metacognition skills). Educational psychologist Paul Pintrich (2000) describes this development 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). Students begin to examine and adjust their thoughts, beliefs, and behaviors by considering their prior technical knowledge and coursework (e.g., mathematics or physics), planning and executing various studying approaches, and managing their time across their entire course load. Although student success in any course is a function of these skills, because engineering mechanics courses represent such an early pivotal point in an engineering curriculum, students' ability to self-regulate learning—and how instructors can help students develop this skill—represents a critical area of further study.

The large class scenario, however, places many constraints on *how* teachers can provide targeted feedback and monitor individual students' progress; this educational environment generally forces teachers to provide minimal individual feedback and instead offer general feedback to the class in the aggregate. When providing feedback on class performance, many instructors will conduct analyses on individual assessments by interrogating class averages and show those results to their students following exams. This approach considers assessments as discrete events (i.e., performance on Test 1, performance on Test 2, etc.). Additionally, many instructors will pay attention to students' cumulative performance, generally placing particular emphasis on this measure at the end of a full course (i.e., students' final grades in a class). However, both of these approaches lose information about students' "academic performance paths" through the class (i.e., a holistic view of grades over time). If it is important to help students develop self-regulation skills, such as identifying effective strategies and planning to improve in a course after a poor grade, then understanding how those paths change from one assessment to the next represents an important consideration. We explore this idea in our study of students enrolled in large engineering mechanics courses, specifically Statics, and address the following research question:

> **RQ 1:** What academic performance paths exist in an undergraduate mechanics course?

After establishing predominant academic performance paths, we investigate how students with different paths differ on a suite of measures related to students' self-reported learning strategies for engaging with course content as well as their final exam performance. The objective of this analysis was to determine whether recommending that teachers pay attention to students' academic performance paths—as opposed to discrete grades or only final averages—might provide insights on how students approach learning within large classes. We addressed the following:

> **RQ2:** How do overall performance and student learning strategies differ across academic performance paths in an undergraduate mechanics course?

Review of the Literature

The middle years of undergraduate engineering study are formative years that introduce students to foundational engineering and discipline-specific coursework. The limited prior work that has investigated the middle years has focused on redesigning curriculum and instruction formats to address student persistence and instructional challenges (Lord & Chen, 2014). Still, researchers acknowledge the need to further investigate academic experiences and outcomes in the middle years, as most research in engineering education has focused on students' first and final years as undergraduates. We contribute to the literature focused on engineering students' middle years by exploring the relationships between student learning strategies and students' academic performance paths over the duration of a semester in a foundational engineering course.

Student Learning Strategies

A vast body of literature has demonstrated the key role that learning strategies play in student learning. From a cognitive perspective on learning, all students must become independent learners, be able to engage in continuous learning, and take control of their own learning (e.g., Bransford et al., 2000; Greeno, Collins, & Resnick, 1996; Newstetter & Svinicki, 2014). Conceptualizations of constructs such as "self-regulation" or "metacognition" within the engineering education literature have varied (Lawanto, 2010), including a range of phenomena such as awareness of knowledge, thinking, learning, and organizing cognitive resources (e.g., Cuasay, 1992; Flavell, 1979; Marzano et al., 1988). Although our study investigates domain-specific student learning strategies, the theoretical backing for exploring learning strategies is strongly informed by literature on metacognition, self-regulation, and metalearning—thus these are discussed in this review.

As summarized by Meyer et al. (2015a), previous research on metacognition within engineering education has shown the following benefits for students: (1) helping them recognize how to associate elements of knowledge, (2) promoting long-term comprehension of concepts, (3) developing self-confidence, (4) increasing awareness of their own knowledge gaps, and (5) enabling teachers to provide students with actionable metacognitive feedback. There has been widespread focus on how metacognitive abilities play an important role in problem-solving and knowledge transfer, as students aim to apply their expertise within different contexts (Lawanto, 2010; McKenna, Johri, & Olds, 2014; Prince & Felder, 2006; Woods, 2000). Litzinger et al. (2010), for example, identified this pattern when evaluating weak and strong students' approaches to solving free body diagrams in a statics course. The academically stronger students utilized metacognitive skills nearly twice as much as did the academically weaker students in a Statics course. Other authors across a range of engineering disciplines similarly have shown a relationship between metacognitive abilities and academic performance in chemical engineering (Ko & Hayes, 1994), statics (Hanson & Williams, 2008), and civil engineering (Meyer et al., 2015a). Previous researchers have linked metacognitive skills and abilities to higher grade point average, expert and novice practices (Larkin, McDermott, Simon, & Simon, 1980; Voss, Greene, Post, & Penner, 1983), enhanced problem-solving (Cooper, Sandi–Urena, & Stevens, 2008) and higher average exam scores (Zulkiply, Kabit, & Ghani, 2009). Thus, literature supports the connection between students' metacognitive activities and their learning and performance in courses.

Captured under this broad "metacognition" umbrella, metalearning refers to the more specific notion that individuals have awareness of their own approaches to learning and their abilities to control it. As articulated by Biggs (1985), metalearning consists of two stages: awareness of learning processes within a specific learning context (i.e., how am I learning?), and self-regulatory (internal) control over those processes (i.e., how can I develop a successful learning strategy?). As argued by Meyer et al. (2015b) within the undergraduate engineering context, for students to develop metalearning capacity they need to become aware of their learning behaviors via some mechanism, they need help interpreting those existing behaviors, and they need to be empowered to change their behaviors. All of these efforts should be focused within a specific learning context because approaches to learning vary contextually.

Researchers within engineering education have taken a few different approaches to developing students' metalearning capacities. Some researchers have advocated for a student success program specifically focused on metalearning (e.g., Turner, 2001), but that kind of approach does not sit within the context of students' engineering coursework. Other approaches have included administering self-report instruments such as the Study Process Questionnaire to explore differences in students' surface and deep approaches learning across courses and class years (Jenkins, Edwards, Nepal, & Bolton, 2011; Turner, 2004). In a more recent advancement, Meyer et al. (2015b) administered the Reflections on Learning Inventory within a Civil Engineering course in Australia and focused students' learning contexts on a specific "threshold concept" in the course. Using this tool helped make learning within a specific context visible for students via an individually tailored learning profile that yielded benefits in learning engagement and conceptual understanding, as indicated by student participants. Literature on the awareness and self-regulatory control of the thinking and learning process sets the stage for our focus on student learning strategies, as self-regulation is a process that involves goal-setting, planning, motivation, monitoring, appropriate help-seeking, evaluation, and reflection (Ormrod, 2012). These characteristics of self-regulated learning are reflected in strategies adopted by engineering students in their learning, including independent problem-solving, working with peers, and attending office hours (McCord & Matusovich, 2013).

While we are not measuring metalearning capacity specifically, our study similarly investigates a mechanism for helping students visualize how academic performance paths correspond to student learning strategies. We investigate how leveraging a commonly used measure (i.e., grades) in a new way might serve as an indicator of students' learning processes to open up new dialogue between instructors and about metalearning in a large, middle years engineering course. In this work, we evaluate students' performances on tests across the semester, investigate their performance paths within the course, and compare those paths for differences in time spent on different learning strategies as well as final course grade. We capture data using surveys administered around high-stakes exams throughout the semester to help students think about their learning processes. Although researchers have used similar in-class survey approaches before and after lectures (Mazumder, 2012; Mazumder & Ainsworth, 2010), we instead investigate how learning strategies relate to longitudinal course performance to understand how students might adjust within the time window of a single semester. Understanding this relationship provides a mechanism for instructors to understand and explain to students how behavior can be adjusted throughout a course to support successful academic performance in undergraduate engineering courses.

Data and Methods

Data Collection Context

This study took place during the 2014–2015 academic year at a comprehensive, research-intensive university in the United States that is predominantly known for its College of Engineering. The institution enrolled about

7,000 undergraduate engineers during that year across all class years. Data for this study were drawn from four sections of the Statics course (two in Fall 2014 and two in Spring 2015) that were all taught by the same instructor for consistency of pedagogical style. The Statics sections were taught in a lecture style that followed a common course schedule across all sections and instructors within the department, but individual instructors had autonomy in determining their approaches to teaching. Linear Algebra and Vector Geometry are prerequisites for the course, and Mutivariable Calculus is a co-requisite. Following institutional review board (IRB) procedures for involving students in research projects, enrolled students were given the option to participate in this study and allow their exam data to be incorporated in analyses. Table 1 gives a demographic breakdown of the consenting study sample, which suggests that it is a reasonable demographic representation of the broader College of Engineering population.

Table 1. Demographic breakdown of consenting student sample compared to recent college enrollment

	Consenting Sample (n=191)	College of Engineering Enrollment
Sex		
Female	28%	22%
Male	72%	78%
Racial/Ethnic Background		
African American	2%	3%
Asian/Pacific Islander	12%	12%
Hispanic/Latino	3%	5%
White (Non-Hispanic)	78%	62%
Multi-Racial	3%	4%
Prefer Not to Answer/None of the Above	3%	2%
Nonresident Alien[a]	---	11%

Note: Numbers may not total 100% because of rounding to nearest integer.
[a]The nonresident alien category is reported in the institutional data but was not used as a category in our research.

The class's assessment scheme included 24 homework problem sets (accounted for 15% of the grade in total), four high-stakes tests (each accounted for 15% of the total grade with each test set by the instructor), as well as a final, common departmental exam (weighted at 25% of the total grade). The four high-stakes tests, which were written by the instructor, consisted of four to seven open-ended problems similar to assigned homework exercises, and were graded by awarding partial credit when incorrect answers were characterized by common identifiable mistakes within otherwise conceptually sound solutions. In contrast, the departmentally written and standardized final exam consisted of multiple choice-style problems (i.e., about 20 individual questions drawn from 10-14 problems) with no partial credit awarded for incorrect answers. For example, if a problem required solving for forces in a truss system, the truss system would comprise one problem but may include several individual questions to report values for different variables.

Data Sources and Collection Procedures

Outside of the course performance, this study consisted of five online surveys collected over the course of the semester via Qualtrics. The first survey was administered at the beginning of the semester, included basic demographic questions, and solicited overarching consent for researchers to link together participant course performance with any other research data collected (e.g., future surveys). The remaining four surveys were identical to one another and administered the class period prior to each of the high-stakes tests in the course. These surveys, hereafter named according to the high-stakes test which they preceded (e.g., Pre-Test 1 Survey), explored how often (i.e., hours per week) and through what methods (e.g., classroom attendance, office hours, independent problem solving, group problem solving) students self-reported engagement with course content throughout the semester. These items were not from existing instrumentation in the literature but instead leveraged the instructor's expertise to understand common ways in which students engage with course content. An open-ended question prompted respondents to consider indicating methods of engagement not specifically named in the survey but did not result in any submissions that suggested the surveys warranted substantive revision. The means of engagement included in the surveys also aligned with existing research that examined intentional ways that students engage in the learning process in the context of conceptual change (McCord &

Matusovich, 2013). Students were given time to complete the surveys during class meetings, and 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.

Responses from the surveys were paired with course achievement data (homework average, high-stakes tests 1-4, final exam, overall course grade). The total number of student responses decreased throughout the course, which we attribute to students withdrawing from the course, survey fatigue, and dissatisfaction with overall course performance. Out of a population of 477 students enrolled in the sections at the start of each semester, responses on the various surveys were: 202 students (42.3%) on the first survey, 182 (38.2%) on the Pre-Test 1 Survey, and 85 students (17.8%) on the Pre-Test 2 survey. Response rates on surveys corresponding to Tests 3 and 4 were low enough to warrant dropping those from our analyses due to concerns that the sample would no longer be representative across all academic performance paths. Thus, we focus on linking course-long performance data with the student learning strategies reported on the Pre-Test 1 survey and the Pre-Test 2 survey.

Analytical Procedures

Our first research question focused on the identification of academic performance paths across multiple tests; to identify such paths and group together students who exhibited similar performance paths, we utilized cluster analyses. We first performed agglomerative hierarchical cluster analysis on scores from the four high-stakes tests using the built-in *hclust* function in R and identified the number of clusters desired using guidance from the *hclust* dendrogram. Having identified the number of clusters, we then used the partitioning around medoids (*pam*) function from the *cluster* package in R to identify cluster membership for each individual student. Partitioning around medoids is a more robust form of commonly used *k*-means clustering methods and is advantageous in part because it does not rely on randomly seeded centroids and thus offers solution stability across analytical runs (Kaufman & Rousseeuw, 2009).

After developing clusters that represent different academic performance paths through the course, we addressed the second research question by examining differences across clusters on other measures related to achievement, engagement, and motivation. With the intent of running analysis of variance (ANOVA) and appropriate post-hoc testing, we examined the distribution of our various dependent variables across the groupings. In most cases, Bartlett's test indicated heterogeneity of variance; consequently, one-way Welch's *F*-tests were used instead of the usual parametric *F*-tests in traditional ANOVAs (Field, Miles, & Field, 2012). Accordingly, when conducting pairwise *t*-tests as part of post-hoc testing to compare group means, we assumed unequal variance and also adjusted *p*-values for family-wise error rate using the Holm correction to the traditional Bonferroni method (Holm, 1979). Though one-way tests are considered robust against the normality assumption, because some of the clusters have relatively small numbers of members (e.g., 10-15) for some dependent variables, the appropriateness of parametric tests is called into question. To interrogate this issue, non-parametric Kruskal-Wallis tests with Dunn post-hoc tests and Bonferroni adjustment for family-wise error rates were completed for all the same comparisons as the one-way tests. In all cases, a threshold of $p<0.05$ was used as the criterion for statistical significance. Across the board, the omnibus tests (i.e., Welch's *F* and Kruskal-Wallis) were in agreement on statistically significant findings for all variables. The post-hoc tests across both were in near-perfect agreement with the rare inconsequential borderline cases (e.g., values slightly above 0.05 on one test and slightly below on another).

Results

Academic Performance Paths, Not Discrete Academic Performance Points (RQ1)

Our cluster analysis sought to identify emergent groupings of undergraduate engineering mechanics students based on their multiple test performances over a semester. We identified a five-cluster solution as best fitting our data using guidance from a dendrogram from the first-stage hierarchical clustering, and proceeded to run a five-cluster partitioning around medoids analysis. We labeled these five clusters as: high performer, average performer, low performer, early adapter, and late adapter. Results of this analysis are shown in Figure 1 as a plot of mean performance on each of the four high-stakes tests broken out by cluster.

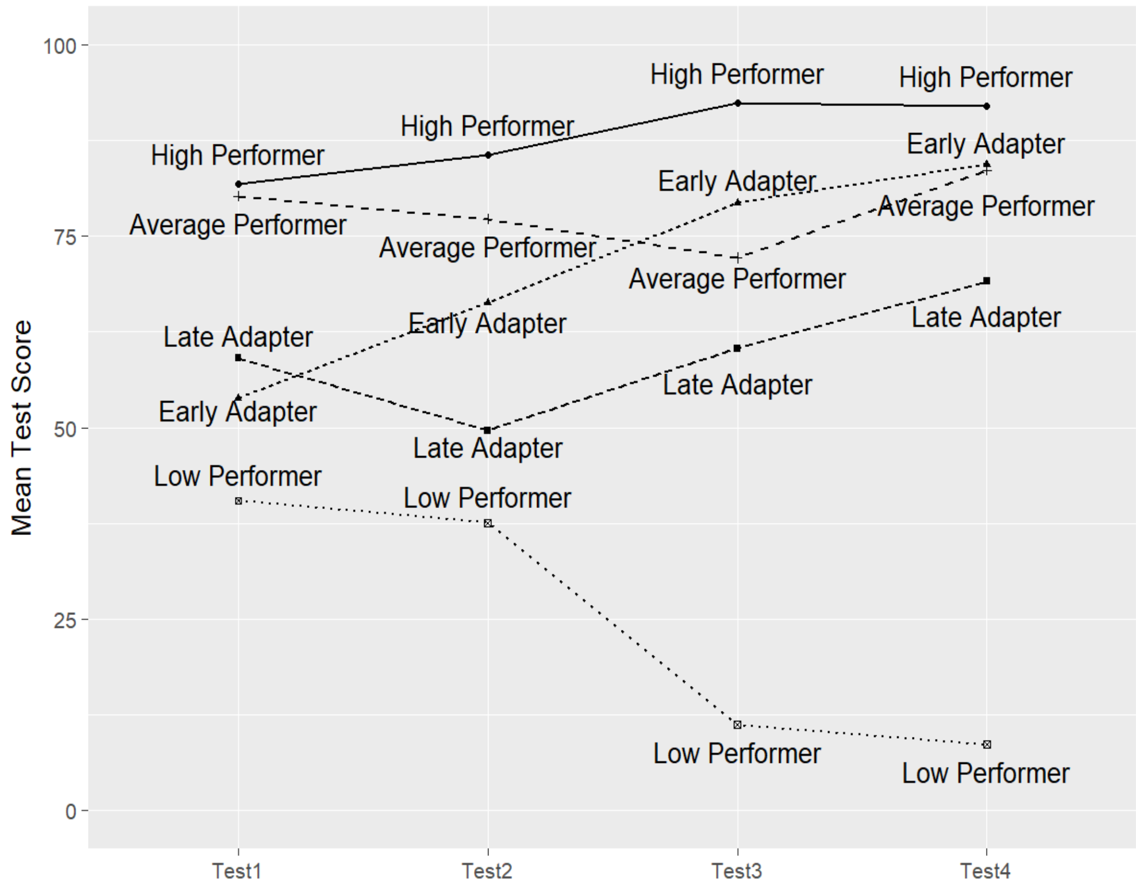

Figure 1. Academic performance paths in Statics based on cluster analysis across four high-stakes tests

We named the clusters to characterize the performance paths over the course of the semester. The High Performer (*n*=71), Average Performer (*n*=104), and Low Performer (*n*=14) clusters are the most intuitive clusters as they represent consistent performance of A's, C's, or F's across each of the four tests. Of particular interest are the Early Adapter (*n*=103) and the Late Adapter (*n*=58) clusters because they exhibit significant variation across the semester. The Early Adapter cluster has a failing Test 1 average (53.81%) followed by a consistent improvement throughout the semester and ends with an overall average grade right at the C- break point, which is the minimum grade for passing the course. On the other hand, the Late Adapter cluster has a slightly better Test 1 average compared to the Early Adapter cluster (59.06%), but instead takes a second poor performance by also failing Test 2 before starting an improvement on Tests 3 and 4. Visualizing students' academic paths in such a way presents a very different picture to instructors and students compared to analyses of single-point exam grades. The Early Adapter and Late Adapter paths would not have been identified when performance is considered discretely as opposed to holistically.

Characterizing Overall Course Performance and Student Learning Strategies by Performance Path (RQ2)

Performance

Course performance is a composite of each high-stakes test and the final exam. However, the cluster solution presented in answering RQ1 was developed on high-stakes test performance for Tests 1, 2, 3 and 4 only. Before investigating this broader performance across the course by performance path (cluster), we first justify exclusions from the cluster analysis. Overall grades offer a summative performance point but were not included in the cluster analysis because they are direct artifacts of the test scores themselves. Similarly, scores on a comprehensive final exam should be related to scores on the individual tests and thus warrant examination by performance path (cluster) but would not warrant including them as a singular input beside each individual test in the data-driven clustering algorithm.

Table 2 includes the numeric values from Figure 1 along with the Final Exam scores and Overall Grades for the class. Additionally, the table includes data for a sixth grouping of students, named "Drop-Out"—this group includes any student who did not fully complete the course and thus was not included in the cluster analysis because of incomplete data. Though not part of the cluster analysis, results about this group's learning strategies will be compiled with the other five clusters because the Drop-Out group remains a critical group of students to understand better.

Table 2. Average performance on each test, the final exam, and final grade by cluster

Clusters	*N*	Test1	Test2	Test3	Test4	Final Exam	Overall Grade
High Performer	71	81.80	85.54	92.34	92.01	80.92	87.01
Average Performer	104	80.20	77.22	72.16	83.61	60.91	74.78
Early Adapter	103	53.81	66.28	79.33	84.33	58.00	69.83
Late Adapter	58	59.06	49.60	60.33	69.11	39.14	56.64
Low Performer	14	34.68	31.77	9.61	7.39	11.00	17.61
Drop-Out	127	43.71	39.60	35.03	--	--	--

The next set of results relies on variables collected through the battery of surveys conducted throughout the course. The number of student responses varied over time, as shown in Table 3. Overall, each cluster is well represented across surveys, which helps mitigate concerns that arise when respondents are overwhelmingly from the same group (e.g., had only the strongest students participated in the research, it would have been difficult to draw conclusions). Across the administration of the Pre-Test 1 and Pre-Test 2 surveys, the Pre-Test 2 Survey received the poorer overall response rate, but there were sufficient numbers of responses in most clusters to allow statistical comparisons. One exception occurred in the Low Performer cluster, which did not have any respondents to the Pre-Test2 survey and thus was not used. It is not surprising that students in that group did not engage in the final survey for the course given their course performance.

Table 3. Response rates to surveys across performance path clusters

Clusters	*N*	Initial Response	Pre-Test 1 Response	Pre-Test 2 Response
High Performer	71	43.7%	39.4%	24.0%
Average Performer	104	33.7%	33.7%	14.4%
Early Adapter	103	54.4%	51.5%	28.2%
Late Adapter	58	53.5%	32.8%	19.0%
Low Performer	14	28.6%	28.6%	0.0%
Drop-Out	127	35.4%	33.9%	10.2%

Student Learning Strategies

We first explore how students self-reported spending their time engaging with course content prior to high-stakes Test 1 (Table 4) and Test 2 (Table 5) independently; next, we consider their time linked across surveys and consider how students changed their time from one part of the class to the next (Table 6). Statistically significant ($p<.05$) differences across the clusters from the series of one-way F-tests are highlighted in gray.

First, looking across Tables 4 and 5 of total hours per week for engagement in specific learning strategies, it seems that the vast majority of students in all groups attended class for the three nominal credit hours (officially 150 minutes of contact time) per week and otherwise invested significant time in the course as shown. For example, students' time engaging with the course ranged from 7.7-11 total hours per week prior to Test 1. These empirical data run counter to the knee-jerk reaction by many instructors that attributes poor performance on a high-stakes exam to lack of student engagement or preparation—the "*you all just didn't work hard enough*" narrative. Surprisingly, the significant differences across clusters are not in the total time spent alone for Test 1 or Test 2 as one might expect, but rather *how* that time is spent.

In preparation for Test 1 (Table 4), a key difference was apparent in time spent solving problems with peers, $F(4,73.7) = 8.40$, $p<0.001$. Students in the High Performer cluster spent the least amount of time on average (0.55 hours per week), and students in the Drop-Out cluster spent the most (2.06 hours per week).

Table 4. Average hours per week spent engaging with course content in the weeks leading to high-stakes test 1

Clusters	Pre-Test Survey 1 Response	Class Attendance	Reading Text	Online	Solving Problems Independently	Solving Problems w/ Peers	Office Hours	Total Time
High Performer	28 (39.44%)	2.75	0.64	0.41	3.36	0.55	0.27	7.69
Average Performer	35 (33.65%)	2.71	1.61	0.89	3.06	1.77	0.66	10.70
Early Adapter	52 (51.46%)	2.72	1.00	0.66	2.52	1.61	0.71	9.25
Late Adapter	19 (32.76%)	2.71	1.53	0.63	2.50	1.84	0.26	9.47
Low Performer	4 (28.57%)	3.00	1.25	0.75	3.00	0.00	0.00	8.00
Drop-Out	43 (33.86%)	2.72	1.66	0.93	2.57	2.06	0.84	10.92

Statistically significant findings related to time activities prior to Test 2 (Table 5) support the notion that the more time students spent engaged in solving problems independently ($F(4,34)= 8.96$, $p<0.001$) is related to higher scores overall. Post-hoc analysis of the Welch's F-test result revealed statistically significant differences between the High Performer cluster (6.47 hours per week), the Late Adapter (2.64 hours per week), and Drop-Out Clusters (1.54 hours per week) in solving problems independently.

Table 5. Average hours per week spent engaging with course content in the weeks leading to high-stakes test 2

Clusters	Pre-Test Survey 2 Response	Class Attendance	Reading Text	Online	Solving Problems Independently	Solving Problems w/ Peers	Office Hours	Total Time
High Performer	17 (23.94%)	2.88	0.50	0.29	6.47	0.68	0.69	11.31
Average Performer	15 (14.42%)	2.77	2.23	1.03	4.27	1.47	0.67	12.43
Early Adapter	29 (28.16%)	2.66	1.30	1.09	4.19	2.83	1.36	13.55
Late Adapter	11 (18.97%)	2.64	2.05	0.68	2.64	3.23	0.77	12.00
Low Performer	0 (0.00%)	--	--	--	--	--	--	--
Drop-Out	13 (10.24%)	2.81	1.96	0.58	1.54	2.77	0.31	10.04

The essence of this finding is repeated again in Table 6 when investigating how different students in different clusters changed the amount of time spent on various activities. Once again, we found statistically significant differences in the change in time spent solving problems independently, $F(4,31) = 4.16$, $p<0.01$; post-hoc tests identified differences between the High Performer cluster (increase in time spent working independently by 2.81 more hours per week on Test 2 than Test 1) and Drop-Out Clusters (0.82 fewer hours per week). We also found a significant difference in the Total Time change from Test 1 to Test 2, $F(4,30) = 2.80$, $p<0.05$, with the Early Adapter cluster making the largest increased investment of total time on average (4.39 hours per week).

Table 6. Change in how time is spent engaging with course content reported in hours per week between high-stakes tests 1 and 2[1]

Clusters	Combined Survey Response	Class Attendance	Reading Text	Online	Solving Problems Independently	Solving Problems w/ Peers	Office Hours	Total Time
High Performer	16 (22.54%)	-0.06	-0.11	0.03	2.81	0.16	0.43	3.12
Average Performer	13 (12.50%)	0.00	0.15	0.08	1.08	0.15	0.23	1.69
Early Adapter	28 (27.18%)	-0.11	0.43	0.50	1.52	1.41	0.70	4.39
Late Adapter	11 (18.97%)	-0.09	0.45	0.09	0.23	1.82	0.32	2.82
Low Performer	0 (0.00%)	--	--	--	--	--	--	--
Drop-Out	13 (10.24%)	0.00	0.77	-0.45	-0.82	0.73	-0.55	-0.23

[1] Note: negative values indicate a decrease in time; positive values indicate an increase.

Discussion

The findings from this study lead us to suggest several implications for improving the educational environment of this Statics course that may also be considered for other large foundational engineering courses. Similarly, our work leads us to consider important next steps in the research to further understand the importance of metalearning, particularly in the pivotal middle years of the undergraduate engineering curriculum.

One key finding in answering RQ1 is the existence of academic performance paths that exhibit significant grade variation on high-stakes tests throughout the semester. In particular, the grade pattern differences between the Early Adapter and Late Adapter clusters demonstrate that two groups with failing grades on Test 1 take different patterns—one resulting in steady improvement and a successful overall grade in the course, and one where any improvement comes too late and results in a failing overall grade in the course. Statics is a challenging foundational course often taught in a high-stakes large lecture environment, and studies have shown that it serves as a gatekeeping course that can be a barrier to student success in engineering (e.g., Grohs, Kinoshita, Novoselich, & Knight, 2015; Grohs, Soledad, Knight, & Case, 2016). From the perspective of faculty members and administrators, there is an expectation that students may struggle in challenging foundational courses as they adapt to the academic demands of the engineering curriculum. However, from the point of view of students who are under-performing in one of their first engineering courses after excelling in high school, that first failing test grade can be distressing and demoralizing. Identifying academic performance paths in a foundational undergraduate engineering course, and specifically the existence of the Early Adapter compared to the Late Adapter cluster, can provide a hopeful, yet sobering, reflective opportunity for students because it positions how students respond to their Test 1 performance as a potential fork in the road. Instructors can show these kinds of performance path data to students so that they can see how large numbers of students have recovered from a poor first test and finished with a passing grade. Other students who do not begin to improve until after their second test grade were unable to recover in time and did not pass the course.

If nothing else, such a result should demonstrate to students the importance of help-seeking and adjustment of strategies—engaging in metalearning—earlier rather than later in a course. While we cannot know exactly what caused the differences between the academic performance paths, we believe that instructors can play a key role in prompting student reflection by encouraging students to consider their grade after Test 1, to set goals for what feasible grades on future tests may be, and to think about the means of engaging with course content that can enable student learning and success. These suggestions are supported by literature and thus our work offers reinforcement; for example, findings about the MUSIC Model of Academic Motivation have shown giving students actionable ways they might drive their own learning, and demonstrating faculty investment in student success both increase student academic motivation (Jones, 2009). The knowledge of academic performance paths where students show dramatic improvement over the course of the semester may inspire improvement by demonstrating that it is not only possible, but that many students routinely make such improvement semester after semester.

Other important findings from this work stem from questions prompted by findings in RQ1—what behavior is different across these clusters? Do students across clusters engage in different ways or for different amounts of time? To address these questions, we used the survey information about specific learning strategies students used and the amount of time they invested in the course across these strategies. Although we cannot make any causal claims that may be desired by a student facing the fork in the road between Early Adapter and Late Adapter, an investigation of variation across clusters lends insight into what students in stronger-performing clusters may do differently than their less successful peers. In a participatory design study exploring how data may assist students be more successful, first-year engineering students specifically brainstormed such comparative analyses as something they desired. In particular, they wanted to know how high-performing students were different in terms of variables like time spent engaging in different class-related activities (Knight, Brozina, & Novoselich, 2016).

A key finding was that students across all academic performance paths reported investing significant time in the course, including classroom attendance. This result is somewhat surprising in a large, challenging gatekeeper course where it is expected that significant numbers of students will not be successful. Narratives rationalizing dropout in gatekeeper courses often depict a body of students as too unwilling to work hard enough to be successful. Olson and Riordan (2012) note that "many STEM faculty members believe that this 'weeding out' process is in the best interest of their disciplines and the larger national interest." Shifting these narratives is important, especially given that they may contribute to reasons why gatekeeping courses have been shown to disproportionally hinder women and underrepresented groups (e.g., Gainen, 1995; Seymour, 2008). Our research contribution, that all groups are investing significant time, may come as a surprise to the "weed-out" notion that students just aren't working hard enough to be successful. Instead, as noted in our results, the critical difference appears to be in how students invest their time.

Time spent solving problems with peers, in the context of this course and this assessment structure, was a learning strategy employed differently by the different clusters. In advance of both Test 1 and Test 2, the High Performer cluster of students spent the least amount of time solving problems with peers, while students in less academically successful clusters such as the Drop-Out or Late Adapter clusters spend significantly more. At first glance, this finding could seem to go against established positive benefits of social learning and collaboration with peers (e.g., Doolittle, 1997; Gallagher, Weldon, Haller, & Felder, 1999). However, the testing environment required students to solve problems in an independent manner on a challenging, timed exam. Although collaboration may often benefit learning, the testing environment of this course specifically, and of foundational engineering courses at large institutions generally, is in sharp contrast to solving problems with peers. Further, individuals struggling to learn content may be lured into a false sense of security about what they know when working with groups since recognizing rationales behind solution steps is different than generating them on one's own. Aligned with best practices for cooperative learning, instructors should encourage students to engage in metacognitive processes to pay close attention to what they do not fully understand without the assistance of their peers.

Time spent solving problems independently was another student learning strategy that differed significantly across academic performance pathway clusters. The High Performer cluster spent the most amount of time solving problems independently in preparation for Test 2 and also invested a significantly larger increase in time on this activity from Test 1 to Test 2 when contrasted with learning strategy investment shifts other clusters made from Test 1 to Test 2. For example, the Drop-Out cluster actually decreased the amount of time invested in solving problems independently but increased other strategies such as solving problems with peers. Though time investment in a course need not be a zero-sum game, we characterize this behavior as a doubling down on a seemingly less effective strategy by the Drop-Out cluster that is noteworthy and warrants further study.

These findings about solving problems independently highlight it as a student learning strategy that appears to be particularly important for student success in this Statics course. We have already argued that, at face value, solving problems independently in practice is in strong alignment with the mode of performance—sitting alone in one's room with a calculator and a problem on a blank page is a great way to prepare for a test consisting of 5 or 6 problems on a blank page without aids. Additionally, the highlighted importance of solving problems independently as a mode of engagement is supported by broader literature on the role of practice in learning. Specifically, research has shown that deliberate goal-directed practice is critical to learning and expertise as compared to more general types of practice (Ambrose, Bridges, DiPietro, Lovett, & Norman, 2010; Ericsson, Krampe, & Tesch-Römer, 1993). Arguably, independently solving problems is the most goal-directed means of engagement that students reported with obvious end results of problems being solved, or not, solely attributable to the learner's efforts. Thus, it is more about working smarter rather than just working harder.

Limitations and Future Work

These findings should be interpreted with a few cautions. First, the sample sizes decrease when the overall number of survey responses is broken down into respondents from each of the different clusters. In part because steps were taken to choose conservative post-hoc procedures to account for family-wise error issues in multiple pairwise comparisons, larger sample sizes (i.e., more statistical power) would be needed to interrogate more helpful differences between the Early Adapter and Late Adapter clusters and thus shed insight on the "fork-in-in road moment" for those groups of students. As a further limitation, self-reported data about course engagement could be artificially inflated because of social desirability bias, although IRB consent documents indicated that research findings would only be reported to the instructor in aggregate during the course and thus any bias would not be a result of a respondent concern for individual judgement about responses. Additionally, the magnitude of hours students reported investing in course-related efforts across the different kinds of activities differed as anticipated, so we have more confidence in these values. For example, the low averages for office hour attendance resonated with what the instructor experienced.

Both students and instructors may be interested to know how much time on average students spend engaging with course content. In our study, the instructor was surprised that students from all clusters were reporting that they invest significant time in the course. Further, how little time some students were spending solving problems independently was also a surprise and prompted explicit discussion in class about ways for students to construct and attempt their own practice exam of problems from the textbook as formative assessments to gauge readiness for the next high-stakes test. Although not consistently implemented in this administration, basic analysis procedures for the course engagement questions could be automated by the research team so that an instructor could share the hours per week across engagement strategies data with the overall grade distribution following each test. Students are accustomed to comparing their own grades to the grade distribution of the whole class, so pairing grade data with engagement data could assist students in proactively shifting strategies and improving performance throughout the semester.

A primary goal of this research has been to make student learning strategies and class performance paths more visible to faculty and students alike. To address limitations associated with large foundational engineering courses noted in the introduction, one highlight of this work is the ability to capture students' engagement in real time so instructors might have actionable recommendations to adjust their own teaching, and to present the data to students as an opportunity for opening a discussion around metalearning. Though this study was limited to one instructor of several large Statics sections, future work should focus on similar data collection across varied instructors and related foundational engineering courses to gain a better understanding of how our findings might relate to similar courses and contexts.

Acknowledgements

The authors would like to gratefully acknowledge the support of a 4-VA Collaborative Research Grant, which supported the research in this article.

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