International Journal of Engineering Education Vol. 36, No. 4, pp. 1340–1355, 2020
Printed in Great Britain
0949-149X/91 $3.00+0.00


# Engineering Students' Performance in Foundational Courses as a Predictor of Future Academic Success*

KYLE M. WHITCOMB[1], Z. YASEMIN KALENDER[1], TIMOTHY J. NOKES-MALACH[2], CHRISTIAN D. SCHUNN[2] and CHANDRALEKHA SINGH[1]
[1] Department of Physics and Astronomy, University of Pittsburgh, Allen Hall, 3941 O'Hara St, Pittsburgh, PA 15260, USA.
E-mail: kmw136@pitt.edu, zyk2@pitt.edu, clsingh@pitt.edu
[2] Learning Research and Development Center, University of Pittsburgh, LRDC, 3939 O'Hara St, Pittsburgh, PA 15260, USA.
E-mail: nokes@pitt.edu, schunn@pitt.edu

Math and science courses (physics, chemistry and mathematics) are considered foundational in engineering curricula and all engineering undergraduates must successfully complete courses in these subjects. However, relatively little is known about the predictive relationships between foundational math/science/engineering coursework and later engineering courses. This study uses large-scale institutional data to investigate the relationships between grades earned in foundational courses and early engineering courses in two large majors in order to gain insight into which foundational courses are most predictive of later performance and whether the relationship follows a linear or threshold function. Multiple regression analyses were performed on course grades using 10 years of data on 5,348 engineering students to construct a predictive model. We find that the predictive relationship between early and later performance is generally linear rather than threshold and that the strongest predictors are advanced mathematics courses along with cumulative STEM GPA, which is in turn strongly predicted by high school GPA and entry test scores. Physics and introductory engineering programming and modeling courses from the first year also predict performance in later courses. Advanced mathematics courses are critical to the long-term success of engineering students in these two common majors and students should be encouraged to aim for high rather than minimally passing grades.

**Keywords:** engineering curriculum; academic advising; equity; mathematics; predictive model

## 1. Introduction

### 1.1 Background and Theoretical Framework

Relationships among courses are critical in the design of a curriculum, especially for interdisciplinary fields such as engineering that integrate many areas of science and mathematics. Further, there can be a struggle to fit all requisite foundational courses into earlier coursework (whether in upper secondary or early university) while also allowing for interest-based exploration. Knowledge of strong relationships between foundational courses and later coursework can support overall curriculum revision efforts as well as personalized learning decisions. Furthermore, it is important to quantitatively investigate how performance in these courses correlates with later performance in the curriculum in order to confirm the assumptions that these courses are foundational to a successful education in engineering. Evaluation of the strength of course relationships in an existing curriculum can be accomplished using educational data mining of large institutional data and learning analytics. In this paper, we present a methodology for implementing such learning analytics with existing institutional data and apply the methodology to the data from one US-based institution to test foundational questions about the nature of predictive relation between first year science and mathematics and later engineering courses. While the study is implemented within one US-based engineering program, the broader methodology described can be applied to curricula at any institution.

Engineering schools are increasingly recognizing the importance of evidence-based approaches to improve student learning and ensure that all students have the opportunity to excel regardless of their background [1–6]. In addition, preparing a diverse group of engineers who are able to embrace the challenges and opportunities of the 21st century is essential to strengthening the Science, Technology, Engineering, and Mathematics (STEM) workforce. Meeting these goals requires that institutions take a careful look at the extent to which engineering education is equitable and inclusive and provides adequate support, advising and mentoring to all students from diverse backgrounds who have traditionally been left out to ensure that even those students who had less than ideal opportunities at the K-12 level have the opportunity to excel in engineering undergraduate programs.

Making appropriate changes to curricula based upon data requires holistic consideration of how an undergraduate engineering school is currently succeeding, including how prior foundational courses



* Accepted 10 February 2020.

predict future performance in engineering courses. Such information can be useful regardless of the theory of change an engineering school adopts and implements. At the same time, with advances in digital technology in the past decade, data analytics can provide valuable information that can be useful in transforming learning for all students [7, 8].

Much prior research on engineering education has focused on: (1) evidence-based classroom practices to improve various facets of learning [9], (2) how to evaluate the effectiveness of different pedagogical approaches [10, 11], and (3) the balance of teaching theory and practice [12]. But there has been much less focus on how student performance in different subsequent courses builds upon prior courses. Information obtained from data analytics on large institutional data in these areas can be an important component of understanding, e.g., the role foundational courses play in later engineering performance as well as contemplating strategies for strengthening these ties, and improving student advising, mentoring, and support.

Studies of curricula as a whole have focused on more general outcomes such as enrollment, degree attainment, and retention rates within engineering programs [13–19]. Of particular relevance is the extensive research conducted using the Multiple-Institution Database for Investigating Engineering Longitudinal Development (MIDFIELD) [20–22]. The MIDFIELD dataset is a rich source of curricular data that allows for multi-institution investigations into how students across engineering fields and from different demographics (e.g., women and underrepresented racial and ethnic minorities) thrive throughout a curriculum and the relative frequency at which they complete their degrees and obtain engineering jobs [23–30].

A yet under-explored question is how well do foundational engineering, science, and mathematics courses (which are sometimes considered weed-out courses) predict performance of students in later engineering courses. Because of the variation across institutions in foundational course requirements [31], this kind of investigation naturally begins with an investigation of a particular engineering school's first-year curriculum. Such an investigation can be useful for other institutions that may perform similar analyses (but adapted to their required foundational curricula) in order to contemplate strategies for improving engineering education in a holistic manner. We hypothesize that some lessons may prove to be quite general since there is considerable overlap in foundational courses. For example, early required coursework in physics and mathematics is very similar in most countries, although these may be completed during upper secondary rather than first year of the engineering degree in some countries. Within most large US engineering programs, the more specific structure of required foundational courses is more consistent. These foundational courses are required under the assumption that the later engineering courses would build on these subjects. Below, we summarize other relevant prior research literature before laying out our research questions.

### *1.2 Relevant Prior Literature Review*

Very few studies to our knowledge have focused on the relationships between specific science and mathematics courses and subsequent engineering courses using large data analytics. Those few studies have focused on aspects of course relationships such as, in the case of Reeping, Knight, Grohs, and Case [32], enrollment patterns and grades earned by students repeating courses. One analogous study focused on science course outcomes and explored the relationship between foundational science and mathematics courses taken in high school and performance in introductory college science courses in biology, chemistry, and physics [33]. These researchers used a linear regression analysis with the number of years of high school instruction in each of these subjects as well as mathematics as the independent variables and course performance in introductory college science courses as the dependent variables. They found that the years of instruction in each subject predicted student college success in that same subject, but the only cross-disciplinary correlation was the years of instruction in mathematics predicting performance in every introductory college science course. However, it is possible that these introductory college science courses were taught in a way that made few assumptions about past learning. A different result may emerge for the relationship between foundational courses and engineering courses.

From the student perception side, a number of studies have noted that engineering students often question the relevance of foundational courses to the work of engineers [34, 35]. In particular, engineering students display mixed perceptions of the importance of mathematics to their studies in engineering [36, 37], while engineering faculty members, who perceive various topics in mathematics to be important to an education in engineering, perceive that engineering students graduate with insufficient competency in these topics [38]. Further, this doubt of relevance of foundational science and mathematics courses induces motivational problems for engineering students that then lead to poor course performance and attrition [13]. Having empirical evidence for the relevance of foundational courses to later engineering coursework using large institutional data and subsequently conveying these findings to the students has the potential to improve student motivation.

There can be many reasons why there may not be a transfer of knowledge acquired in one course to improved performance in a later course that is theoretically related [39]. First, the actual overlap in terms of specific knowledge and skills can be minimal (e.g., the main area of overlap may be the last part of the foundational course which could be treated as an optional special topic). Second, there can be superficial differences in the way key concepts and skills are discussed or represented (e.g., notational differences for how derivatives or energy are represented) that prevent students from discerning connections between courses. There is a large literature in the cognitive and learning sciences showing that students often fail to spontaneously transfer relevant conceptual knowledge and skills to novel problems with new surface features or those presented in different contexts [40–43]. Third, the instruction in either the foundational course or the later courses may not frame the knowledge and skills that are being learned in general ways that lead students to be more likely to generalize and make connections [44]. Thus, there may be an empirical foundation to students' belief that foundational coursework is not actually helpful for later engineering coursework.

On a related matter, there is the question of the form of the relationship between courses, which is important for effective model building but also has practical consequences. The simplest possible forms of course relationships are threshold and linear functions. Many universities require a minimum letter grade of C in order to move on in a sequence (or a mid-level exam outcome in the case of advanced coursework taken in secondary, such as Advanced Placement courses in the US). Informally, students sometimes provide practical advice to each other that only a C is even needed in order to succeed in later coursework ("Cs get degrees") [45, 46]. Each of these is suggestive of a possible threshold function in which higher performance above a certain level (e.g., an A rather than a C or B) does not translate into higher performance in later courses. Alternatively, the relationship among courses may be linear. Huang and Fang [47] compared four different predictive models of academic performance with multiple linear regression as the simplest model and found no significant advantage of the other models over multiple linear regression for predicting the academic performance of large groups of students.

A central methodological issue in studying relationships among courses is controlling for the many correlated sources of performance. In addition to examining in parallel the many foundational courses that could influence a given target course (e.g., physics, chemistry, calculus, and a MATLAB foundational course for a target introductory Materials Engineering course), there are also more general student factors such as general intelligence, mathematical skill, overall study skills, and general academic motivation. In particular, performance in any one course is expected to be correlated with performance in any other course simply by virtue of these more general factors (e.g., students with high academic motivation may perform at higher levels in most courses). Such general factors can be modeled and controlled for in regressions using indictors of general knowledge, motivational, and general academic skills such as high school GPA, performance on the SATs, and cumulative university GPA. For example, Huang and Fang [47] found that the best predictor for a second-year engineering dynamics course was the students' cumulative GPAs, although they also found that grades in prerequisite courses mattered above and beyond cumulative GPA.

### *1.3 Goals and Research Questions*

The current effort develops and tests an approach to using basic statistical techniques on large longitudinal institutional datasets that are increasingly being made available for researchers and practitioners to address problems of both theoretical and practical consequence. Our research focuses on building predictive models for a wide range of foundational engineering curriculum courses in each semester through the first two years using the data from one mid-sized, research-intensive university in the US. Furthermore, we investigate these predictive relationships for selected courses from the two largest engineering departments (or disciplines), namely Mechanical Engineering and Materials Science (MEMS) and Electrical and Computer Engineering (ECE). These courses are typically thought to rely heavily on mathematics and physics (i.e., are especially likely to have concerns about poor student performance in later coursework because of earlier weak performance). Understanding the hierarchy of predictive relationships from foundational courses to subsequent engineering courses provides a useful context for curricular evaluation and advising students as they progress through the first two years of instruction in engineering.

For the two engineering disciplines we focused upon, our research questions (RQs) to guide the investigation are:

**RQ1.** Do foundational course grades relate via a linear, threshold, or some other function to grades in later engineering curriculum courses?

**RQ2.** To what extent does student performance in foundational courses predict performance in second-year engineering courses above and beyond general student performance factors?

**RQ3.** Which foundational courses are most important to course achievement in core second-year engineering courses?

In addition to individually addressing important theoretical and practical questions, as a sequence, these RQs also address the systematic development of appropriate statistical models, moving from working out appropriate functional forms to testing larger patterns of course relationships.

## 2. Methodology

### *2.1 Participants*

Using the Carnegie Classification of Institutions of Higher Education [48], the university at which this study was conducted is a public, high-research doctoral university, with balanced arts and sciences and professional schools, and a large, primarily residential undergraduate population that is full-time, more selective, and low transfer-in. Deidentified application information and course grades data were provided by the university on all first-year engineering students who had enrolled from Fall 2009 through Spring 2018. This data provision is part of a larger NSF-funded inter-departmental effort towards improving education at the university, and the form of the data is similar to the MIDFIELD dataset. The full sample for the current study consists of 5,348 engineering students, identified by having taken either of the introductory engineering courses. The subset of this sample for analyses into the second-year curriculum of two engineering departments consisted of 2,825 students, which includes all students who took at least one third-semester engineering course listed in Table 1 in addition to the introductory engineering courses. The full sample of students includes 27% female students and had the following race/ethnicities: 80% White, 8% Asian, 5% African American, 2% Latinx, and 5% Other. The mean age at the beginning of the student's first year was 18.9 years (SD = 1.7 years), reflecting a population of students who were predominantly attending college immediately after completing high school.

### *2.2 Curricular Context*

This study is primarily focused on the engineering curriculum of the Department of Mechanical Engineering and Materials Science (MEMS), one of the largest engineering departments, to produce statistically robust results. One course is also considered from the Department of Electrical and Computer Engineering (ECE) because the department offers a parallel version of a course on circuits in a different order relative to mathematics courses than the

**Table 1.** The relevant portions of the MEMS and ECE curricula along with shortened names used in other tables and figures and total sample size (*N*) for each course, along with which majors require the course. Bolded are the target second-year engineering courses. Semesters 3 and 4 are further divided into MEMS and ECE

| Semester | Full Course Name | Short Name | *N* | Contributing Engineering Majors |
|---|---|---|---|---|
| 1 | Basic Physics for Science and Engineering 1 | Phys 1 | 5,003 | All |
| | Introduction to Engineering Analysis | Engr 1 | 5,348 | All |
| | Analytic Geometry and Calculus 1 | Calc 1 | 4,214 | All |
| | General Chemistry for Engineers 1 | Chem 1 | 4,767 | All |
| 2 | Basic Physics for Science and Engineering 2 | Phys 2 | 4,069 | All |
| | Introduction to Engineering Computing | Engr 2 | 4,435 | All |
| | Analytic Geometry and Calculus 2 | Calc 2 | 4,009 | All |
| | General Chemistry for Engineers 2 | Chem 2 | 3,706 | All |
| 3 (MEMS) | Analytic Geometry and Calculus 3 | Calc 3 | 3,703 | All |
| | Introduction to Matrices and Linear Algebra | Linear Algebra | 2,572 | Bioengineering, ECE (term 5 or 6), Industrial, MEMS |
| | **Materials Structure and Properties** | **Mat. Structure** | 1,582 | Chemical, Industrial, MEMS |
| | **Statics and Mechanics of Materials 1** | **Mechanics 1** | 1,995 | Bioengineering, Chemical, Industrial, MEMS |
| 3 (ECE) | **Linear Circuits and Systems 1** | **ECE Circuits** | 803 | ECE |
| 3 (ECE) / 4 (MEMS) | Differential Equations | Diff Eq | 3,607 | All |
| 4 (MEMS) | **Statics and Mechanics of Materials 2** | **Mechanics 2** | 851 | MEMS |
| | **Electrical Circuits** | **MEMS Circuits** | 775 | MEMS |

MEMS circuits course; a comparison of performance across these courses enables a robust test of foundational course presence/absence that is not confounded with selection artifacts (e.g., the students that delay foundational courses typically have other challenges). The curriculum analyses focus on year 1 (foundational courses, including two engineering courses designed to teach students MATLAB, C++, and Python) and year 2 (additional foundational courses in mathematics and core discipline-specific engineering), where the connections to foundational courses are potentially most robust and students are most likely to struggle.

Table 1 shows the relevant portions of these curricula, including the first-year courses taken by all engineering students and the selected second-year courses in engineering and mathematics (the only foundational topic that extends beyond the first year in MEMS). Table 1 also shows the number of students within the sample that took each of the courses whose predictive relations are analyzed in this study. In principle, all of the first-year courses are required for all engineering students; however, in practice this is not always the case. A student may lack a grade in the data for many reasons, ranging from skipping the course with Advanced Placement (AP) credit or taking the course at another university. Since not all of these students will have taken the remaining courses used in the study, Table 1 provides an upper bound on the $N$ for statistical tests used because we employ list-wise deletion for our analysis, which will drop a student from a given analysis if the student is missing any one of the variables. Some courses, such as Statics and Mechanics of Materials 1, appear in multiple engineering curricula which may have different requirements for second-year mathematics courses; the sample size ($N$) for statistical analyses involving these courses will be substantially reduced depending upon which courses are included as predictors since each participant in a given model is required to have data for all variables.

### 2.3 Measures

*High school academic achievement*. From the information submitted by the students as part of their applications to the university, the university provided several key pieces of data that are commonly used by universities in the US in admission decisions (because they are predictive of success in university coursework). High school grade point average (HS GPA) is the mean grade across all high school courses (grades 9–12) on a weighted 0–5 scale, which involves adjustments to the base 0–4 scale for AP and International Baccalaureate courses. These adjustments were performed prior to our acquisition of the data. In addition, students take one of two different standardized assessments: the Scholastic Achievement Test (SAT) or the ACT. There are multiple components to each, but we focused on the mathematics achievement component, and converted ACT scores (1–36) into SAT scores (200–800) using the widely available concordance tables provided by the College Board [49]. For the sample of engineering students included in this study, the mean SAT Math score was 690 (SD = 60), and the mean HS GPA was 3.99 (SD = 0.41).

*Grades*. The primary data provided are grade points (GPs) earned in all courses at the university, the semester and specific class section in which each course was taken, and the grade point distributions (mean, sample size, and standard deviation) for each class (used to remove effects of instructor grading variation). GPs are on a 0–4 scale (F = 0, D = 1, C = 2, B = 3, A = 4) where the suffixes '+' and '–' add/subtract 0.25 (e.g., B+ = 3.25) except A+, which has a GP of 4. In order to reduce effects from the particular year and instructor of each course, grade data were "$z$-scored" using the GP earned by the student along with the mean $\mu$ and standard deviation $\sigma$ of the student's specific class section to calculate $z = (\mathrm{GP} - \mu)/\sigma$. The $z$-score is in units of standard deviation. Though the university does allow students to retake courses and replace earlier grades, the data provided to us are the initial raw grade data.

In addition, each student's cumulative STEM GPA was calculated for each semester, defined as the mean GP on all science, engineering, and mathematics courses taken at the university up to that point in time. This measure is meant to capture overall STEM performance as a mixture of general problem solving and reasoning skills, study skills, general motivation in STEM, and engineering-specific competencies. Including such a measure allows the specific value of knowledge and skills derived from foundational courses to be separated from general skills and motivation.

### 2.4 Analysis

*Inclusion criteria*. Engineering curricula have a large number of required courses and relatively little flexibility in the order in which courses are taken due to complex sequences of course prerequisites. Nonetheless, students sometimes take courses earlier than expected (e.g., due to skipping an earlier course based upon advanced high school coursework) or later than expected (e.g., due to failing a core course or taking a reduced course load). The core chronology of the engineering curriculum was used as a filter on included data both to maintain the directionality of the predictive relationships and to inform which attempt should be used if a student attempts a course multiple times: each "target course" that appears includes only students' first attempt of that course, and the semester in which that first attempt occurred was used to select the latest attempt of each "predictor course" that occurred prior to or concurrent with the target course. This chronological enforcement was used in every analysis in this study, all of which contain one target course with one or more predictor variables. Note that the cumulative STEM GPA through one semester prior to the target course was also used as a predictor to control for the general student skills and motivation; we did not use STEM GPA for the whole university degree because predictors generally should not include performances that happen later in time than the dependent variable.

*Qualitative model building*. To get a qualitative sense of the relationships between courses in order to select appropriate statistical models, we generated histograms which first bin students by their letter grade in a predictor course, then within each of those bins, the students are further binned by their letter grade in a target course. Results show no qualitative difference if the mean grade points used are $z$-scored, so the unaltered grade points are used to improve readability. Furthermore, in order to keep the number of bins manageable in this analysis, we grouped together letter grades that differ by a plus or minus sign. For example, the grades B–, B, and B+ were all grouped together as B for some analyses.

*Selecting the appropriate regression function*. In order to determine if the nature of these relationships was a linear, threshold, or some other function (Research Question 1), we also generated graphs plotting the (continuous scale) mean grade points earned in a target course against (discrete) grades earned in various prior or concurrent courses that may predict the target course. These graphs are shown both with and without the +/– distinctions, for example, combining B–, B, and B+ letter grades in predictor courses.

*Model building procedure.* The regression analyses were performed using the "regress" function in Stata version 15.1 [50]. In order to address Research Questions 2 and 3, we sought best fitting multiple regression models [51, 52] with the ($z$-scored) grades of the target course as the dependent variable and ($z$-scored) grades of predictor courses along with general academic performance variables (cumulative STEM GPA, high school GPA, and SAT Math scores) as the independent variables. Note that the list of predictor courses includes all courses taken prior to the target course as well as concurrent mathematics courses. Concurrent mathematics courses have been included since research has suggested there are synergistic benefits to taking concurrent courses utilizing similar content [53]. For target courses, we used the first attempt of the course as the dependent variable, while for predictor courses we used the latest attempt of the course prior to or concurrent with the first attempt of the target course. Initially, all courses prior to or concurrent with the target course were included in the model, and then a modified stepwise-deletion procedure was applied: (1) at each step, the independent variable with the largest $p > 0.05$ was dropped; (2) the regression was re-run with the remaining independent variables; (3) this was done iteratively until all of the remaining independent variables had $p > 0.05$; and (4), because automatic stepwise procedures for model building can get stuck in local minima, each dropped independent variable was put back in the model along with the pared-down list of remaining independent variables in order to ensure that the regression coefficient was not statistically significant (i.e., the previously dropped independent variables' still had $p > 0.05$ when individually reinserted).

The model building procedure was conducted twice for each target course: once without cumulative STEM GPA and once again with it included. Cumulative STEM GPA is meant to control for a general, overall student performance dimension, addressing a combination of study skills, academic motivation, and outside competing pressures (e.g., part-time jobs, hobbies, and family obligations). However, since it is derived from the grades in the predictor courses, it partially also captures knowledge and skills from each foundational course. Thus, including it as a control variable may control too much, potentially producing underestimates of the effects of the foundational courses. Therefore, models with and without this predictor are presented to provide upper and lower bounds on the effects of each foundational course.

From these regression analyses, we report the list of $\beta$ coefficients (standardized to reflect connection strength in effect size units) for significant predictors along with their $p$-values as well as the number of students remaining in each regression, $N$, and the adjusted proportion of variance in the target course explained by the regression, $R^2_{\text{adj}}$ [51–52]. In all models, $R^2_{\text{adj}}$ falls between 0.35 and 0.55 and is less than 0.01 smaller than the non-adjusted $R^2$. Since the best fitting models may include general academic variables, Research Question 2 is addressed by examining the combined standardized beta coefficients of the course predictors. Which course predictors remain significant and their relative strengths as indicated by standardized beta coefficients address Research Question 3.

## 3. Results and Discussion

### *3.1 General Predictive Relationships between Courses*

First, leaving aside for now issues of relative predictive power and controls, every pairing of foundation and target courses showed a positive relationship in that higher foundational course grades were always associated with higher target course grades, with unimodal distributions. There were also interesting variations in the grade relationship distributions found in foundational course-target course pairings. Fig. 1 presents exemplars of the four qualitatively different variations. The differences in these histograms are most readily explained by the standard deviations of grades earned in the target and predictor courses. Fig. 1a shows the target course Materials Structure predicted by Engineering 1, which has a particularly narrow and high grade distribution, leading to an unusually small but highly at-risk population in the C bin. On the other hand, Fig. 1b shows what happens when the target course, in this case Mechanics 1, has a narrow and high grade distribution: As and Bs are generally likely and it is primarily the ratio of As and Bs that is predicted by the predictor course. Finally, Fig. 1c and Fig. 1d show histograms with more typical grade distributions in both target and predictor, whether the predictor course has a low mean (Fig. 1c) or a high mean (Fig. 1d), indicated by the relative number of As, Bs, and Cs in the predictor course.

These kinds of figures may provide information that is useful for advising, especially Fig. 1d in which over half of the students who received a C in Linear Algebra (term 3 in the MEMS curriculum) went on to earn a C or worse in MEMS Circuits (term 4 in the MEMS curriculum). There are a few courses for which a C in the foundational course, although technically sufficient to go on to later courses that have it as a prerequisite, provides a strong predictive signal that the student is likely to struggle in that

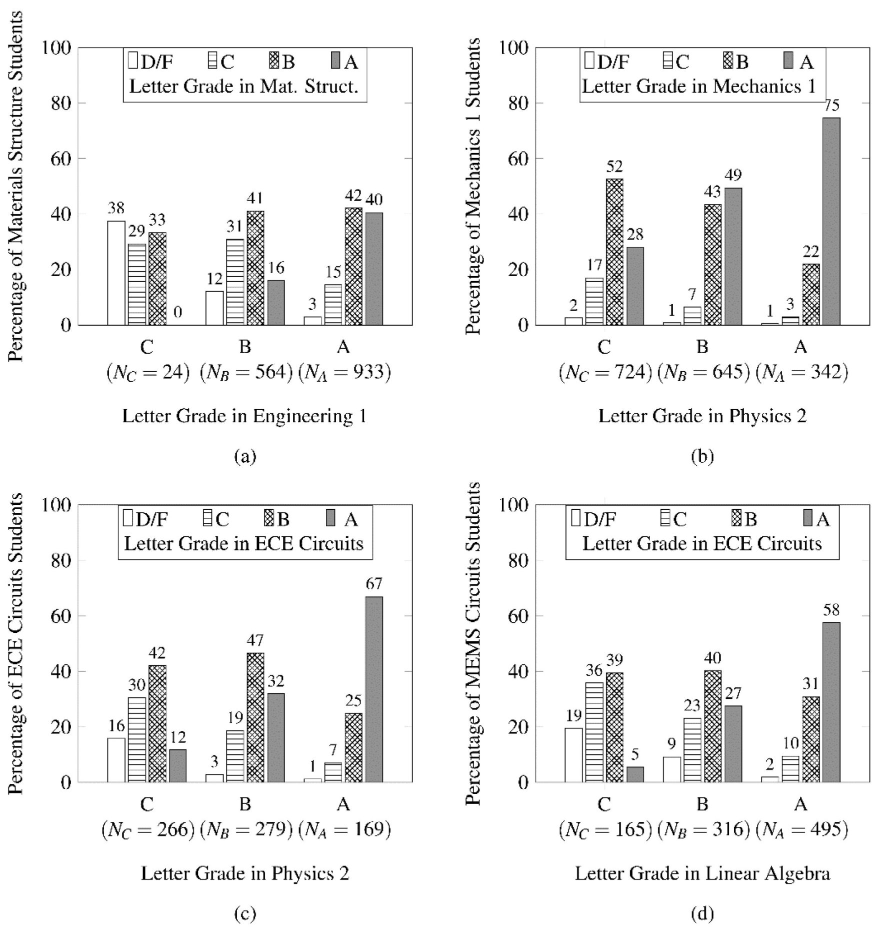


**Fig. 1.** Exemplars of the different relationships between grades earned in pairings of predictor and target courses. Students are binned by their letter grade in the predictor course (horizontal) with the total number of students in each of these three groups ($N_A$, $N_B$, and $N_C$) shown below the letter. The percentage of each group that went on to earn an A, B, C, or D/F in the target course (vertical) is shown in the group of four bars above their grade in the predictor course. Each subfigure shows a different predictor and target pair indicated on the axis labels.

target course and therefore will likely need extra assistance. Academic advisors can also use this kind of information with their advisees to help motivate students to take the prerequisite courses more seriously. That being said, it is important to be careful to always use such data constructively, and in particular to avoid profiling students and contributing to low student competency beliefs, which may be the underlying problem.

### *3.2 Testing Linear or Threshold Functions*

To better understand the nature of these relationships and answer Research Question 1, we examined line graphs for all foundation-target pairings, as is shown for Mechanics 1 as a target course in Fig. 2. We binned students by their letter grade in the predictor course, as was done for the histograms in Fig. 1, but then plotted the mean grade points earned by members of each bin in the target course rather than the full distribution. We observe from these line graphs that the relationships are linear, which is especially clear when the bins are widened by removing plus and minus signs from letter grades to reduce measurement error; there were often large error bars associated with rarely given +/– grades). In every predictor-target course pairing, the relationships displayed similarly clear linearity. Note that the widened grade bins in Fig. 1 and Fig. 2b were used solely for this diagnostic purpose – the linear regression analyses used the more fine-grained grade data.

### *3.3 Model Building Results*

Knowing that the courses are related linearly, multiple regression models were built using linear functions with the list of predictors consisting of high school GPA, SAT Math score, cumulative STEM GPA through the previous term, each prior course in the curriculum, and concurrent second-year mathematics courses. The results of the final predictive models for each target course were examined in terms of the standardized beta coefficients ($\beta$) to answer Research Questions 2 and 3. These $\beta$ coefficients are standardized to range from –1 to 1, though all of the $\beta$ coefficients we find in this study are positive; the values are similar to Pearson correlation values [51, 52]. Table 2 reports the regression results for each of the target second-year engineering courses in this study. In addition to the $\beta$ coefficients, Table 2 reports the $p$-value of each $\beta$ coefficient as well as the $N$ and $R^2_{adj}$ for each regression.

These results are reported both with and without the STEM GPA term included. Comparing these two sets of results, it is clear that chemistry, present only in the regressions without STEM GPA, was acting as a proxy for general factors (e.g., student ability or general academic motivation) while physics, mathematics, and engineering courses remain as predictors in both versions. This asymmetric reduction of $\beta$ coefficients with the inclusion of a measure of general skills shows that these results are measuring the effects of these courses (in physics, mathematics, and engineering) beyond general

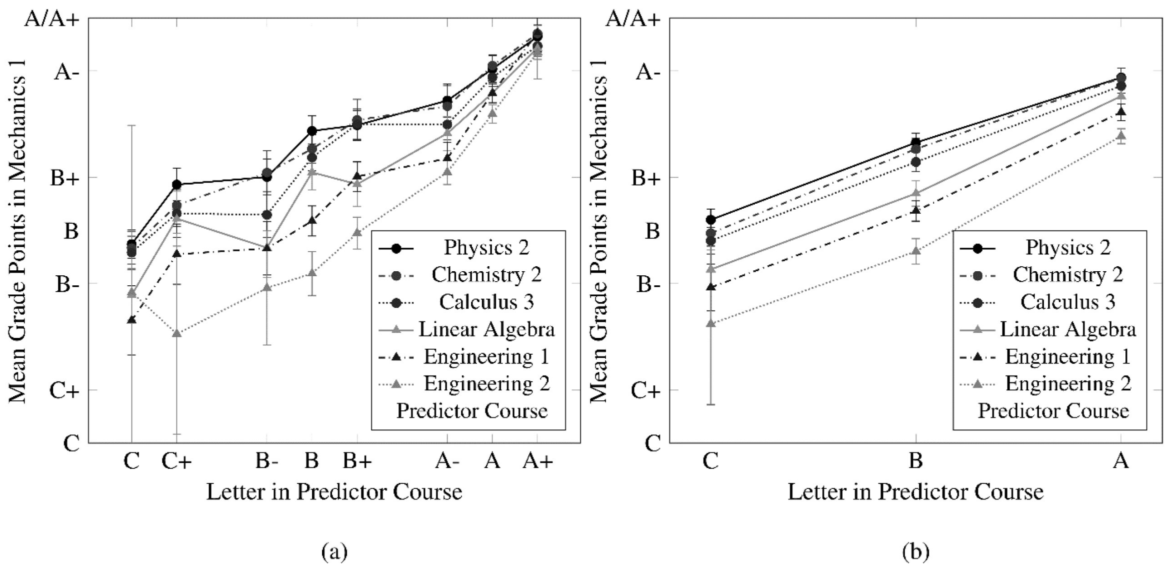


**Fig. 2.** Examining the nature of course relationships (linear, threshold, etc.) in order to inform statistical models. Students are binned by their letter grade in the predictor course (horizontal), then the mean grade points earned in the target course by the students in each bin are plotted vertically along with the standard error. The spacing of letter grades corresponds to the university's grade point values. This linear trend holds for every target/regressor pair in our analysis. Subfigure (a) shows the students binned by all letter grades, while subfigure (b) groups all students who earned, for example, C-, C, and C+ into a single C group.

**Table 2.** Results from the multiple linear regression analyses predicting selected second-year engineering courses. The numbers reported are the standardized $\beta$ coefficients and $p$-values ($^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$). Each target second-year engineering course corresponds to two columns, with regressions run both with and without cumulative STEM GPA as an independent variable. "N/A" entries were excluded in the regressions because they occurred later in the curriculum; "–" entries were included but not statistically significant. Variance Inflation Factors (VIFs) are reported for the STEM GPA predictor as well as the maximum for all other predictors

| | **Targets** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **ECE Circuits** | | **Mat. Structure** | | **Mechanics 1** | | **Mechanics 2** | | **MEMS Circuits** | |
| **Regressors** | **No GPA** | **GPA** | **No GPA** | **GPA** | **No GPA** | **GPA** | **No GPA** | **GPA** | **No GPA** | **GPA** |
| Phys 1 | – | – | – | – | – | – | – | – | – | – |
| Phys 2 | $0.15^{***}$ | $0.12^{**}$ | $0.16^{***}$ | $0.13^{***}$ | $0.10^{**}$ | $0.10^{***}$ | $0.08^{*}$ | – | $0.10^{**}$ | – |
| Engr 1 | $0.17^{***}$ | $0.09^{*}$ | $0.11^{**}$ | $0.07^{*}$ | $0.09^{*}$ | – | – | – | – | – |
| Engr 2 | – | – | – | – | $0.13^{**}$ | $0.11^{***}$ | – | – | – | – |
| Calc 1 | – | – | – | – | – | – | – | – | – | – |
| Calc 2 | – | – | – | – | – | – | – | – | – | – |
| Calc 3 | N/A | N/A | $0.18^{***}$ | $0.16^{***}$ | $0.21^{***}$ | $0.14^{***}$ | – | – | – | – |
| Linear Alg. | N/A | N/A | $0.26^{***}$ | $0.25^{***}$ | $0.23^{***}$ | $0.23^{***}$ | $0.17^{***}$ | $0.13^{***}$ | $0.20^{***}$ | $0.15^{***}$ |
| Diff. Eq. | $0.41^{***}$ | $0.35^{***}$ | N/A | N/A | N/A | N/A | $0.38^{***}$ | $0.27^{***}$ | $0.35^{***}$ | $0.27^{***}$ |
| Mechanics 1 | N/A | N/A | N/A | N/A | N/A | N/A | $0.15^{***}$ | $0.09^{**}$ | N/A | N/A |
| Chem 1 | – | – | – | – | – | – | $0.13^{***}$ | – | $0.10^{*}$ | – |
| Chem 2 | $0.12^{**}$ | – | $0.13^{**}$ | – | $0.11^{**}$ | – | – | – | $0.11^{**}$ | – |
| SAT Math | – | – | – | – | – | – | – | – | – | – |
| HS GPA | – | – | – | – | – | – | – | – | – | – |
| STEM GPA | N/A | $0.25^{***}$ | N/A | $0.18^{***}$ | N/A | $0.19^{***}$ | N/A | $0.35^{***}$ | N/A | $0.37^{***}$ |
| $N$ | 495 | 634 | 650 | 836 | 817 | 1063 | 599 | 735 | 632 | 706 |
| $R^2_{\mathrm{adj}}$ | 0.42 | 0.44 | 0.38 | 0.40 | 0.39 | 0.38 | 0.50 | 0.53 | 0.43 | 0.46 |
| Max VIF (other than STEM GPA) | 1.70 | 1.94 | 1.67 | 1.97 | 1.79 | 1.84 | 1.75 | 1.97 | 1.80 | 1.88 |
| STEM GPA VIF | N/A | 3.47 | N/A | 4.00 | N/A | 3.16 | N/A | 3.08 | N/A | 2.33 |

skills and other general factors that influence student performance.

There is a natural categorization of the results of Table 2 dependent on the semester in which the target course is taken. For the semester 3 courses (ECE Circuits, Materials Structure, and Mechanics 1), the hierarchy of predictors is second-year mathematics first, followed by STEM GPA, followed by a second second-year mathematics course if taken, followed by introductory engineering and physics courses. For the semester 4 courses (Mechanics 2, MEMS Circuits), STEM GPA has risen to be the top predictor followed by two second-year mathematics courses, then in the case of Mechanics 2 the last regressor is Mechanics 1, the prior course in the sequence. These trends indicate that the transfer of specific skills, at least in terms of what can be measured by this type of model, appears to be mostly limited to transfer from one semester to the next but not beyond, with the exception of Engineering 1, which occasionally will predict courses in semester 3 instead of Engineering 2. We note that the content of the introductory engineering sequence is not standardized across institutions, even within the US. At the studied institution, this sequence teaches students computer programming skills in an engineering context.

The magnitudes of the $\beta$ coefficients in Table 2 range from low to medium, and correspondingly the variance explained in the target courses (i.e., $R^2_{\mathrm{adj}}$), ranges from 38% to 53%. This is consistent with the findings shown in Fig. 1, where despite clear trends toward students maintaining similar grades from one course to another, there was some mobility for students. The variance not accounted for by the model may be partially due to the course-grained nature of the grade data itself. In addition, there should also be effects of pedagogical differences between instructors, TA quality, and life events. Still, despite their low to medium size, the majority of the coefficients estimated were highly statistically significant.

In order to test for multicollinearity problems, we followed up these analyses by calculating the Variance Inflation Factors (VIFs) of each regressor, which measure the degree to which the associated regression coefficient variances have been inflated due to collinearity with other independent variables [51, 52]. In every case, the VIFs of all regressors except those for cumulative STEM GPA are below 2.00, including concurrent mathematics courses, while cumulative STEM GPA ranges from 2.33 to 4.00. These values fall well below the commonly cited cutoffs of 10 [52] or the more recent recommendation of 5 [51]. Thus, the data were sufficiently large to overcome the challenges of estimating separable effects of correlated variables.

These multiple regression analyses were done not only with the core engineering courses as target courses, but also for each of the required second-year mathematics courses in the curriculum that could be foundational to other core engineering courses. Using all of these results together, Fig. 3 shows a visual representation of the curriculum with all statistically significant predictive relationships (from the regressions including cumulative STEM

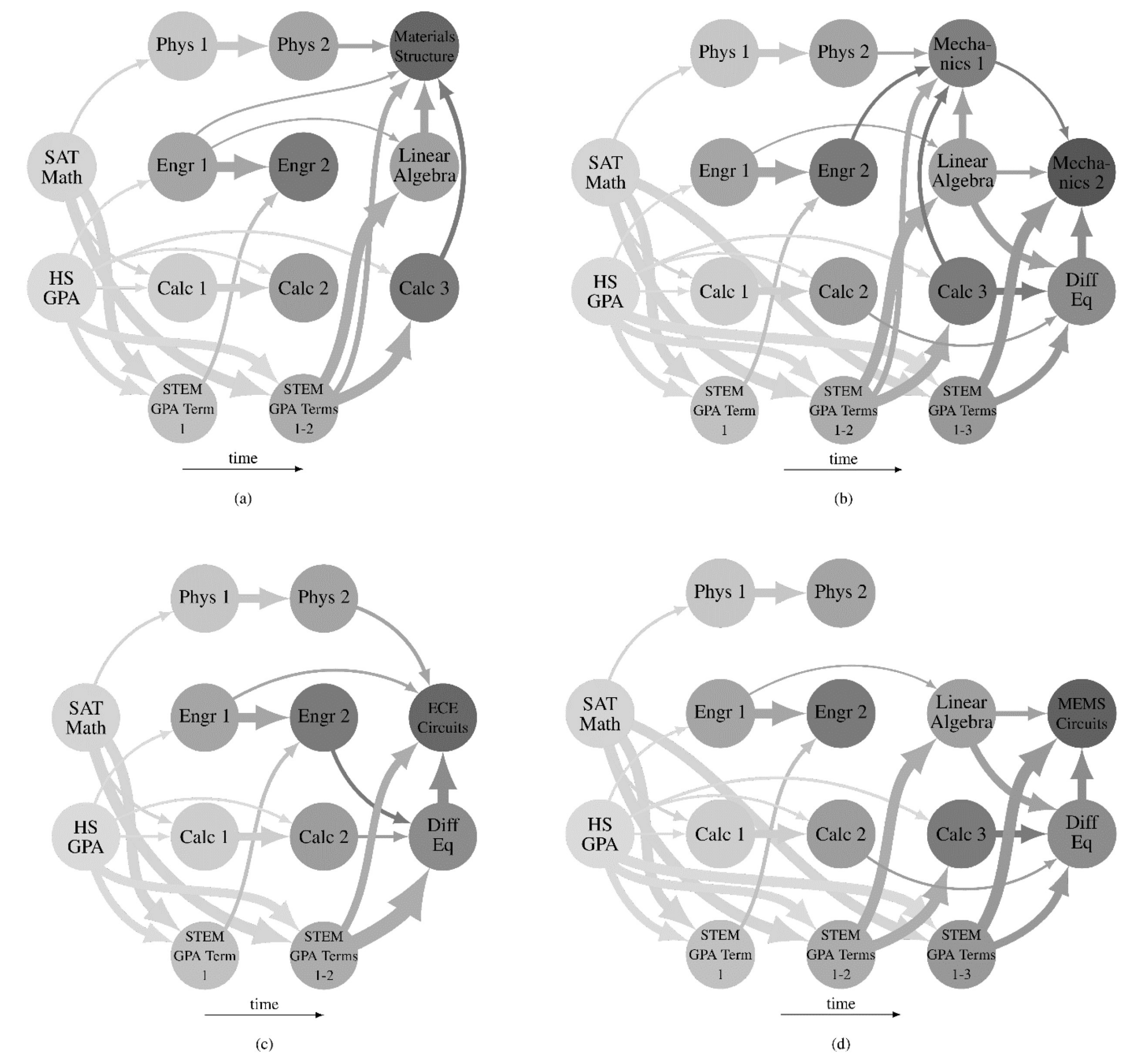


**Fig. 3.** A visual representation of all statistically significant predictive relationships leading to various second year engineering courses: (a) Materials Structure and Properties, (b) Mechanics 1 and 2, (c) ECE Circuits, and (d) MEMS Circuits. Courses are organized left to right according to the chronology of the MEMS and EE curricula. Line thicknesses are scaled directly by $\beta$. Note that since prior STEM GPA values are used directly in the calculation of future STEM GPA values, the prior values are not included as predictors of later values.

GPA) displayed as lines connecting the nodes representing the variables. Chemistry courses are not included in Fig. 3 because they were never statistically significant in the final models once STEM GPA was included; it may be that chemistry is more relevant for core courses in chemistry-oriented engineering majors (i.e., chemical, petroleum, or environmental engineering) in contrast to the core courses in physics-oriented engineering majors that were examined in this study.

A few basic patterns are observable within and between diagrams in Fig. 3. STEM GPA is a large predictor of all second-year courses, potentially because it becomes a more refined general-performance estimate with more courses contributing to it. The SAT Math variable drops out as a direct predictor after the first semester, later acting indirectly "through" STEM GPA. In contrast, high school GPA continues to have a small direct relationship to calculus courses and a large indirect effect through STEM GPA. Similarly, first-year courses can have not only direct effects on target second-year engineering courses, but also indirect effects mediated through the predictor course's effect on some other course that predicts the target. For example, in Fig. 3b we do not see a direct effect of Physics 2 on Mechanics 2, but it does have an indirect effect since Physics 2 predicts performance in Mechanics 1, which predicts performance in Mechanics 2. Finally, with only one exception, there are always direct connections within course sequences (e.g., Physics 1 to Physics

2; Engineering 1 to Engineering 2; Calculus 1 to Calculus 2; Mechanics 1 to Mechanics 2). The one exception is that Calculus 3 is predicted directly by neither Calculus 1 nor 2; here the inclusion of STEM GPA may have produced too conservative an estimate because it includes both Calculus 1 and Calculus 2 grades. However, Differential Equations maintains a connection to Calculus 2, so it may be that some other explanation is required (e.g., the more difficult multi-variate aspects of Calculus 3 are not based on remembering aspects of Calculus 1 and 2).

Addressing Research Question 2, course performance in every second-year mathematics course and every core engineering course is substantially predicted by performance in some foundational courses, above and beyond the predictive role of general student academic performance measures. There is an important predictive role for such a general factor, which is best captured by the STEM GPA and to a smaller extent HS GPA. Indeed, chemistry courses gave spurious connections to courses that have no obvious chemistry content in them until STEM GPA was included in the analysis, while the predictive power of introductory physics and engineering is only slightly reduced. But the cumulative predictive strengths of the foundational courses are large in every case, above and beyond the general factor: sometimes the top foundational course was a stronger predictor than STEM GPA and always the combination of the top two foundational courses were a stronger predictor than STEM GPA (these trends are most easily seen in Table 2 by comparing the regression coefficients).

Turning to Research Question 3 about which courses were most important, we find that university mathematics appears to be a general foundational pillar for engineering students in all their coursework. This result is consistent with the findings of Sadler and Tai [33] that high school mathematics is the general foundational pillar for university students' performance in introductory biology, chemistry, and physics. Note also that different core engineering courses depended upon different mathematics courses. In other words, it was not the case that performance in any single mathematics course is a good general indicator of student skill; rather different core engineering courses depend upon specific kinds of mathematics (Calculus 3, Linear Algebra, or Differential Equations).

The contrast of ECE vs. MEMS Circuits courses (lower two diagrams of Fig. 3) provides an interesting case because the content of these courses and the implementations are very similar according to their syllabi, but the sequence of prerequisite courses in the two majors is different. MEMS Circuits is taken one semester later, after students have taken Linear Algebra. For students in MEMS Circuits, Linear Algebra is a substantial predictor in addition to Differential Equations, which is taken concurrently. This suggests that the students in ECE Circuits may be at a disadvantage for not having had Linear Algebra. In order to test this, we conducted an ANCOVA on ECE Circuits grades based on the order in which Circuits and Linear Algebra were taken (three groups, Linear Algebra before, concurrent, and after or never); although there is a typical order, some students take Linear Algebra earlier than do others. It is important to note that course order is inherently confounded by academic skill; that is, stronger students are more likely to take second-year mathematics courses earlier. Therefore, it is important to control for such prior differences in this analysis. One particularly relevant proxy for mathematical skill is SAT Math score; controlling for SAT Math and high school GPA, we still see a significant benefit in ECE Circuits grade for those who took Linear Algebra prior to or concurrent with ECE Circuits, $F(2, 960) = 4.09$, $p < 0.02$.

Furthermore, these engineering students also rely on their introductory engineering courses in which they learn to use computational tools of engineering beyond mathematics, such as MATLAB, C++, and Python. Again, it is not that one of these serves as a general indicator variable for all core courses. Sometimes Engineering 1 was the significant predictor (i.e., for Material Structures and Linear Algebra in the MEMS curriculum and ECE Circuits in the ECE curriculum) and sometimes Engineering 2 was the significant predictor (i.e., Mechanics 1 in the MEMS curriculum and Differential Equations in the ECE curriculum); which of the two courses remains significant may depend upon what tools the later courses use.

Finally, these engineering students rely on core courses that are directly related to their discipline. For the physics-oriented engineering disciplines MEMS and ECE, that additional foundation is their introductory physics sequence. For example, doing well in the ECE Circuits is unlikely when students obtain Cs in Physics (as highlighted in Fig. 1), even when controlling for mathematics ability and general student ability.

## 4. General Discussion

Consistent with the finding of Sadler and Tai [33] for the transition from high school to college science courses, we find that mathematics is a foundational pillar of success for engineering students as they progress through their engineering curriculum. Our findings are not a simple replication, since the population of our study (engineering students in their first two years of college) is different than the population in Sadler and Tai's study (a variety of college STEM students in their transition from high school to college) and the target courses are different. Further, the variation in which form of mathematics is most important across engineering courses and the existence of predictive power above and beyond general STEM GPA predictors provide even stronger evidence for the role of mathematics course content rather than just a general mathematical ability factor. Consider, for example, the results for the fourth-semester course Mechanics 2 in Table 2 and Fig. 3b, where we delineate the various correlations of the third-semester courses Mechanics 1, Linear Algebra, and Calculus 3 to Mechanics 2. Notably, Calculus 3 is not a significant predictor while Linear Algebra is, showing that the predictive powers measured are sensitive to more than just the discipline and recency of the predictor course. Additionally, Linear Algebra is a stronger predictor of performance in Mechanics 2 (indicated by a higher $\beta$ coefficient) than the prior course in the sequence, Mechanics 1, despite the fact that another mathematics course, Differential Equations, co-occurs as an even stronger predictor of Mechanics 2 while no other engineering courses appear as direct predictors. The current findings provide evidence that the details of the mathematical skills and knowledge *per se* are the foundation of the transfer.

Beyond these relationships between mathematics and engineering, we further found that physics was also a pillar of success for these MEMS and ECE students, albeit with a smaller effect than the concurrent mathematics courses. This relationship between foundational courses in physics and mathematics and subsequent courses in engineering at the college level is fundamentally different from the relationships observed by Sadler and Tai in that they saw no interdisciplinary effect: other than the transfer effects for mathematics, only within-discipline effects were observed. The difference between their findings and ours may partly be due to the depth of knowledge acquired in high school vs. in college and partly to the interdisciplinary, applied-science nature of engineering. This work provides evidence for course specific knowledge and skills transfer effects from foundational courses to later engineering courses. Our findings suggest that these foundational courses offer invaluable contexts for further analysis of transfer. For example, future research could examine particular knowledge and problem-solving skills that students transfer from the foundational courses to subsequent engineering courses from one context to another and what aspects of the curriculum facilitate or hinder such transfer of knowledge.

### *4.1 Implications for Instruction and Future Research*

Our analysis using large institutional data at a large US-based research university validates the inclusion of these foundational courses in engineering curricula by revealing the strength of transfer of knowledge and skills from foundational courses to core courses using a multiple linear regression analysis. Similar analyses should be conducted to examine other engineering departments. While mathematics and physics were statistically significant predictors of performance in engineering disciplines that have a strong emphasis on mathematics and physics, we hypothesize that a similar investigation into chemical engineering curricula is likely to reveal predictive power of introductory chemistry for the subsequent engineering performance of those students. Further, we hypothesize that investigations of this nature by engineering departments at colleges and universities outside of the US would be similarly able to analyze how well their courses build upon one another. This is true for departments with curricula similar to the one described here – with early interdisciplinary courses followed by discipline-specific courses – or even more broadly for curricula which specialize earlier (e.g., in UK-based departments).

This type of large-scale investigation using institutional data to examine the predictive relationships between courses can play a central role in advising engineering students. For example, advisors guiding students through their first two years in an engineering program could benefit from a research-backed understanding of the course relationships in the engineering curricula as well as course performance trends, such as those seen in Fig. 1. We urge advisors using results such as these in a positive manner: to *encourage* students who have enrolled in these foundational courses to take them seriously to promote improvement in course grades, instead of *discouraging* students from pursuing an engineering major. Also, making note of these strong course relationships can help advisors identify potential indicators for a need for additional support. However, these types of additional support should be provided with careful planning in a manner that does not profile students, e.g., by potentially offering the same additional support to all students even though some students are particularly encouraged to take advantage of them.

Research-based evidence from the type of analysis presented in this investigation could be used to counteract problematic common wisdom being circulated among students about some foundational courses being unimportant to later success and that they should only strive to get passing grades. Similarly, departments seeking to (re)-design their curricula can also greatly benefit from this type of investigation because they need to understand the affordances and constraints involving relationships between different courses in the engineering curriculum that most strongly drive student performance. It is logical to wonder what the consequences of replacing these early courses with alternate course designs (e.g., by adding more intense design-project courses) would be; however, our findings suggest that there is a benefit to each of the current courses and it would therefore be unwise to replace the current courses without testing whether the replacement courses provided additional benefits.

Another equally important finding is the nature of STEM GPA as a good predictor of performance in later semesters. The $\beta$ coefficients in Table 2 show that STEM GPA is a stronger predictor in semester 4 courses (MEMS Circuits, Mechanics 2) than semester 3 courses (ECE Circuits, Materials Structure, Mechanics 1). It is important to note that the follow up analysis on the VIFs indicated that STEM GPA is somewhat collinear with the other predictors, though this is expected given how it is calculated. That being said, the time when the STEM GPA is most closely related to the other predictors is in predicting term 2 courses, and STEM GPA is either a non-significant or, in the case of Engineering 2, a weak predictor of performance in term 2 courses. It is only in terms 3 and 4 that the STEM GPA variable becomes a significant and large predictor, perhaps in part because over time it becomes an increasingly sensitive measure relative to individual course grades. Regardless, this trend indicates that in later semesters, students are increasingly likely to perform similar to the way they have performed in the past. In particular, student mobility from a low GPA to high GPA is limited and students who typically obtain C grades in earlier courses are predicted to continue to perform at a similar level in later courses.

This lack of mobility brings up an important issue of equity since students who are less privileged are more likely to have had less than ideal K-12 education and are more likely to have lower grades in college [54]. Ideally, a college academic setting should provide appropriate guidance, mentoring, and support to close the academic opportunity gap and promote growth to ensure that all students develop similar levels of high competency regardless of their performance in the first year. Students who had strong and weak high school GPAs then initially obtained As and Cs, respectively, in the first year. If these two groups continue to perform on parallel trajectories throughout their college education and their performances in the later years do not become comparable, it may signal that the higher education institution may not be doing enough to close this opportunity gap over the years the students are in college engineering programs and ensure that all engineering students have the opportunity to excel and thrive, not just survive. Otherwise, students who complete their engineering degree with a low GPA are unlikely to find good career opportunities that are comparable to those offered to students with high GPAs.

In addition to wider efforts to make education equitable, advisors can play a critical role in supporting students who may be struggling. We again emphasize the importance of avoiding profiling students, which can be accomplished by giving the same advice to all students instead of only to a particular subset. Such advice could draw attention to the importance of students' foundational coursework to success in later engineering coursework. In fact, a recent call for funding to create equitable STEM learning environments in which all students thrive regardless of their background and prior preparation explicitly challenges four year colleges and universities to include "careful consideration of prerequisites" because if there are strong ties between courses and students get behind on the prerequisites, it can hinder learning throughout their undergraduate STEM major [55]. This is particularly relevant in light of prior research showing that engineering students perceive first-year courses as unimportant to their overall academic career [34–37].

Finally, we note that although the relationships reported here by analyzing large institutional data are inherently correlational, we have intentionally designed the selection of data for our regression analyses to enforce the chronology of the MEMS and ECE curricula in order to strengthen the validity of these predictive relationships and we have controlled for high school GPA and SAT Math scores, the strongest likely confounds in this kind of research. However, the inclusion of factors beyond course performance, e.g., survey data measuring engineering students' motivational beliefs about physics, mathematics, and engineering, could further strengthen these claims by providing additional context for what students believe about their own abilities in these various foundational subjects. Moreover, the addition of motivational characteristics as predictors could help isolate how academic performance can be partially based on motivational beliefs rather than entirely based on cognitive skills and content knowledge [56, 57]. Such analyses are critically important for evaluating how equitable current instructional systems are for underrepresented students who may be at increased risk, e.g., for anxiety due to stereotype threats. This type of information can further help one to contemplate strategies for designing equitable and inclusive learning environments. In particular, if correlations are found between these motivational characteristics and academic performance or pathways through a curriculum, then efforts to promote equitable and inclusive learning environments can also include strategies for boosting all students' motivational beliefs because there is a strong tie between these beliefs and student learning [58].

## 5. Conclusions

In this study, we investigated the relationships between grades earned in foundational courses and second-year engineering courses for students in two large engineering majors. We found that course grades in foundational courses relate linearly to grades in later engineering courses, indicating that simple linear regression models were appropriate for such prediction analyses. These regression models revealed that student performance in specific prior courses can be connected to performance in second-year engineering and mathematics courses, even when controlling for several general student performance factors, namely high school GPA, SAT Math score, and cumulative STEM GPA. Further, we found that advanced mathematics courses (i.e., Calculus 3, Linear Algebra, and Differential Equations) along with cumulative STEM GPA, were the strongest predictors of student performance in second-year engineering courses.

*Acknowledgments* – This research is supported by NSF Grant DUE-1524575 and the James S. McDonnell Foundation Grant 220020483. We are grateful to Larry Shuman for helpful discussions and feedback on this research.

## References

1. M. Borrego and J. Bernhard, The emergence of engineering education research as an internationally connected field of inquiry, *Journal of Engineering Education*, **100**(1), pp. 14–47, 2011.
2. M. Borrego and C. Henderson, Increasing the use of evidence-based teaching in STEM higher education: A comparison of eight change strategies, *Journal of Engineering Education*, **103**(2), pp. 220–252, 2014.
3. M. Borrego, R. A. Streveler, R. L. Miller and K. A. Smith, A new paradigm for a new field: Communicating representations of engineering education research, *Journal of Engineering Education*, **97**(2), pp. 147–162, 2008.
4. A. Johri and B. M. Olds, Situated engineering learning: Bridging engineering education research and the learning sciences, *Journal of Engineering Education*, **100**(1), pp. 151–185, 2011.
5. S. Singer and K. A. Smith, Discipline-based education research: Understanding and improving learning in undergraduate science and engineering, *Journal of Engineering Education*, **102**(4), pp. 468–471, 2013.
6. R. A. Streveler, T. A. Litzinger, R. L. Miller and P. S. Steif, Learning conceptual knowledge in the engineering sciences: Overview and future research directions, *Journal of Engineering Education*, **97**(3), pp. 279–294, 2008.
7. R. S. Baker and P. S. Inventado, Educational data mining and learning analytics, in G. Veletsianos (ed), *Learning Analytics*, Springer, New York, NY, pp. 61–75, 2014.
8. Z. Papamitsiou and A. A. Economides, Learning analytics and educational data mining in practice: A systematic literature review of empirical evidence, *Journal of Educational Technology & Society*, **17**(4), pp. 49–64, 2014.
9. T. Litzinger, L. R. Lattuca, R. Hadgraft and W. Newstetter, Engineering education and the development of expertise, *Journal of Engineering Education*, **100**(1), pp. 123–150, 2011.
10. S. L. Eddy and K. A. Hogan, Getting under the hood: How and for whom does increasing course structure work? *CBE – Life Sciences Education*, **13**(3), pp. 453–468, 2014.
11. M. B. Morin, K. M. Kecskemety, K. A. Harper and P. A. Clingan, The inverted classroom in a first-year engineering course, *120th American Society for Engineering Education (ASEE) Annual Conference and Exposition*, Atlanta, 23-26 June 2013, pp. 23.1220.1–23.1220.11, 2013.
12. A. J. Swart, Does it matter which comes first in a curriculum for engineering students – Theory or practice?, *International Journal of Electrical Engineering Education*, **47**(2), pp. 189–199, 2010.
13. M. Besterfield-Sacre, C. J. Atman and L. J. Shuman, Characteristics of freshman engineering students: Models for determining student attrition in engineering, *Journal of Engineering Education*, **86**(2), pp. 139–149, 1997.
14. O. Eris, D. Chachra, H. L. Chen, S. Sheppard, L. Ludlow, C. Rosca, T. Bailey and G. Toye, Outcomes of a longitudinal administration of the persistence in engineering survey, *Journal of Engineering Education*, **99**(4), pp. 371–395, 2010.
15. R. M. Felder, G. N. Felder and E. J. Dietz, A longitudinal study of engineering student performance and retention. V. Comparisons with traditionally-taught students, *Journal of Engineering Education*, **87**(4), pp. 469–480, 1998.
16. K. A. Harper, L. Abrams and J. P. Ruffley, (2014). A longitudinal study of the impact of a first-year honors engineering program, *122nd American Society for Engineering Education (ASEE) Annual Conference and Exposition*, Indianapolis, 15–18 June 2014, 2014.
17. K. L. Meyers, G. W. Bucks, K. A. Harper and V. E. Goodrich, Multi-institutional evaluation of engineering discipline selection, *122nd American Society for Engineering Education (ASEE) Annual Conference and Exposition*, Seattle, 14-17 June 2015, pp. 26.1175.1–26.1175.13, 2015.
18. G. M. Nicholls, H. Wolfe, M. Besterfield-Sacre and L. J. Shuman, Predicting STEM degree outcomes based on eighth grade data and standard test scores, *Journal of Engineering Education*, **99**(3), pp. 209–223, 2010.
19. G. M. Nicholls, H. Wolfe, M. Besterfield-Sacre, L. J. Shuman and S. Larpkiattaworn, A method for identifying variables for predicting STEM enrollment, *Journal of Engineering Education*, **96**(1), pp. 33–44, 2007.
20. S. M. Lord, R. A. Layton and M. W. Ohland, Multi-institution study of student demographics and outcomes in electrical and computer engineering in the USA, *IEEE Transactions on Education*, **58**(3), pp. 141–150, 2015.

21. S. Lord, R. Layton, M. Ohland, C. Brawner and R. Long, A multi-institution study of student demographics and outcomes in chemical engineering, *Chemical Engineering Education*, **48**(4), pp. 231–238, 2014.
22. M. W. Ohland and R. A. Long, The multiple-institution database for investigating engineering longitudinal development: An experiential case study of data sharing and reuse, *Advances in Engineering Education*, **5**(2), pp. 1–25, 2016.
23. C. E. Brawner, M. M. Camacho, S. M. Lord, R. A. Long and M. W. Ohland, Women in industrial engineering: Stereotypes, persistence, and perspectives, *Journal of Engineering Education*, **101**(2), pp. 288–318, 2012.
24. C. E. Brawner, S. M. Lord, R. A. Layton, M. W. Ohland and R. A. Long, Factors affecting women's persistence in chemical engineering, *International Journal of Engineering Education*, **31**(6A), pp. 1431–1447, 2015.
25. S. M. Lord, M. M. Camacho, R. A. Layton, R. A. Long, M. W. Ohland and M. H. Wasburn, Who's persisting in engineering? A comparative analysis of female and male Asian, Black, Hispanic, Native American, and White students, *Journal of Women and Minorities in Science and Engineering*, **15**(2), pp. 167–190, 2009.
26. J. Main, K. J. Mumford and M. W. Ohland, Understanding migration patterns of engineering undergraduates: Major intent, course grades, and major choice, *International Journal of Engineering Education*, **31**(6A), pp. 1468–1475, 2015.
27. Y. Min, G. Zhang, R. A. Long, T. J. Anderson and M. W. Ohland, Nonparametric survival analysis of the loss rate of undergraduate engineering students, *Journal of Engineering Education*, **100**(2), pp. 349–373, 2011.
28. M. W. Ohland, C. E. Brawner, M. M. Camacho, R. A. Layton, R. A. Long, S. M. Lord and M. H. Wasburn, Race, gender, and measures of success in engineering education, *Journal of Engineering Education*, **100**(2), pp. 225–252, 2011.
29. M. W. Ohland, S. D. Sheppard, G. Lichtenstein, O. Eris, D. Chachra and R. A. Layton, Persistence, engagement, and migration in engineering programs, *Journal of Engineering Education*, **97**(3), pp. 259–278, 2008.
30. M. Pilotte, M. W. Ohland, S. M. Lord, R. A. Layton, M. K Orr, Student demographics, pathways, and outcomes in industrial engineering, *International Journal of Engineering Education*, **33**(2), pp. 506–518, 2017.
31. R. L. Matz, B. P. Koester, S. Fiorini, G. Grom, L. Shepard, C. G. Stangor, B. Weiner and T. A. McKay, Patterns of gendered performance differences in large introductory courses at five research universities, *AERA Open*, **3**(4), pp. 1–12, 2017.
32. D. Reeping, D. Knight, J. R. Grohs and S. W. Case, Visualization and analysis of student enrollment patterns in foundational engineering courses, *The International Journal of Engineering Education*, **35**(1), pp. 142–155, 2019.
33. P. M. Sadler and R. H. Tai, The two high-school pillars supporting college science. *Science*, **317**(5837), p. 457, 2007.
34. J. Flegg, D. Mallet and M. Lupton, Students' perceptions of the relevance of mathematics in engineering, *International Journal of Mathematical Education in Science and Technology*, **43**(6), pp. 717–732, 2012.
35. G. Zavala, A. Dominguez, A. C. Millan and M. Gonzalez, Engineering students' perception of relevance of physics and mathematics, *123rd American Society for Engineering Education (ASEE) Annual Conference and Exposition*, New Orleans, 26–29 June 2016, 2016.
36. M. P. Coupland, A. P. Gardner and G. Carmody Jones, Mathematics for engineering education: What students say, *Mathematics Education Research Group of Australasia (MERGA) Conference*, Brisbane, pp. 139–146, 2008.
37. P. Winkelman, Perceptions of mathematics in engineering, *European Journal of Engineering Education*, **34**(4), pp. 305–316. 2009.
38. K. A. Harper, G. R. Baker and D. M. Grzybowski, First steps in strengthening the connections between mathematics and engineering, *120th American Society for Engineering Education (ASEE) Annual Conference and Exposition*, Atlanta, 23–26 June 2013, 2013.
39. D. K. Detterman and R. J. Sternberg, *Transfer on Trial: Intelligence, Cognition, and Instruction*, Ablex Publishing, Norwood, NJ, 1993.
40. M. Bassok and K. J. Holyoak, Interdomain transfer between isomorphic topics in algebra and physics, *Journal of Experimental Psychology: Learning, Memory, and Cognition*, **15**(1), p. 153, 1989.
41. M. L. Gick and K. J. Holyoak, Analogical problem solving, *Cognitive Psychology*, **12**(3), pp. 306–355, 1980.
42. B. H. Ross, This is like that: The use of earlier problems and the separation of similarity effects, *Journal of Experimental Psychology: Learning, Memory, and Cognition*, **13**(4), p. 629, 1987.
43. S. B. Day and R. L. Goldstone, The import of knowledge export: Connecting findings and theories of transfer of learning, *Educational Psychologist*, **47**(3), pp. 153–176, 2012.
44. R. A. Engle, Framing interactions to foster generative learning: A situative explanation of transfer in a community of learners classroom, *The Journal of the Learning Sciences*, **15**(4), pp. 451–498, 2006.
45. E. A. Kuley, S. Maw and T. Fonstad, Engineering student retention and attrition literature review, *Proceedings of the Canadian Engineering Education Association (CEEA)*, Hamilton, Ontario, 31 May–3 June 2015, 2015.
46. E. Kuley, S. Maw and T. Fonstad, Understanding barriers to student success: What students have to say, *Proceedings of the Canadian Engineering Education Association (CEEA)*, Saint John, New Brunswick, 19–22 June 2016, 2016.
47. S. Huang and N. Fang, Predicting student academic performance in an engineering dynamics course: A comparison of four types of predictive mathematical models, *Computers & Education*, **61**, pp. 133–145, 2013.
48. The Carnegie Classification of Institutions of Higher Education, http://carnegieclassifications.iu.edu, Accessed 8 November 2019.
49. Guide to the 2018 ACT® /SAT® Concordance, https://collegereadiness.collegeboard.org/educators/higher-ed/scoring/concordance, Accessed 8 November 2019.
50. L. C. Hamilton, *Statistics with Stata: Version 12*, Cengage Learning, Ringgold, Portland, OR, 2013.
51. D. C. Montgomery, E. A. Peck and G. G. Vining, *Introduction to Linear Regression Analysis*, 4th edn, Wiley-Interscience, Hoboken, N.J, 2006.
52. J. Neter, M. H. Kutner, C. J. Nachtsheim and W. Wasserman, *Applied Linear Statistical Models*, 4th ed, Irwin, Chicago, 1996.
53. M. M. Hurley, (2001). Reviewing integrated science and mathematics: The search for evidence and definitions from new perspectives, *School Science and Mathematics*, **101**(5), pp. 259–268, 2001.
54. P. A. Westrick, H. Le, S. B. Robbins, J. M. Radunzel and F. L. Schmidt, College performance and retention: A meta-analysis of the predictive validities of ACT® scores, high school grades, and SES, *Educational Assessment*, **20**(1), pp. 23–45, 2015.
55. Howard Hughes Medical Institute, Inclusive excellence: Building institutional capacity for student belonging, https://www.hhmi.org/sites/default/files/programs/inclusive/ie3-program-announcement-final.pdf, Accessed 8 November 2019.
56. E. M. Marshman, Z. Y. Kalender, T. Nokes-Malach, C. Schunn and C. Singh, Female students with A's have similar physics self-efficacy as male students with C's in introductory courses: A cause for alarm? *Physical Review Physics Education Research*, **14**(2), p. 020123, 2018.

57. P. Vincent-Ruz, K. Binning, C. D. Schunn and J. Grabowski, The effect of math SAT on women's chemistry competency beliefs, *Chemistry Education Research and Practice*, **19**(1), pp. 342–351, 2018.
58. D. S. Yeager and G. M. Walton, Social-psychological interventions in education: They're not magic, *Review of Educational Research*, **81**(2), pp. 267–301, 2011.

**Kyle Whitcomb** is a PhD candidate in the Department of Physics and Astronomy at the University of Pittsburgh. He obtained his BS in Physics and Mathematics from the University of Puget Sound. His research focuses on promoting equity and inclusion in undergraduate physics education and using statistical methods to identify sources of inequities courses and how these inequities propagate through students' academic careers.

**Z. Yasemin Kalender** obtained a BS degree from Boğaziçi University in Istanbul with a focus on experimental particle physics during which she worked as a collaborator in several projects at CERN. Later, she moved to U.S. to continue her education as a PhD student at the University of Pittsburgh with a research focus on physics education. Her current research interest is investigating motivational characteristics of students, diversity issues in the physics discipline, and incorporating big data analysis techniques into the area of physics education research. After earning her PhD in 2019, she continues her academic training as a postdoctoral research associate at Cornell University.

**Timothy Nokes-Malach** is an Associate Professor of Psychology and a Research Scientist at the Learning Research and Development Center at the University of Pittsburgh. He received his Bachelors degree from the University of Wisconsin-Whitewater, PhD from the University of Illinois at Chicago, and Postdoctoral training at the Beckman Institute for Advanced Science and Technology at the University of Illinois at Urbana-Champaign. His research focuses on human learning, motivation, and knowledge transfer. His work has been supported with grants from the James S. McDonnell Foundation, the Pittsburgh Science of Learning Center, the National Science Foundation, and the Department of Education's Institute for Education Sciences.

**Christian Schunn** obtained his PhD from Carnegie Mellon in 1995. He currently is a Senior Scientist at the Learning Research and Development Center and a Professor of Psychology, Learning Sciences and Policy, and Intelligent Systems at the University of Pittsburgh. Most recently he became Co-Director of the Institute for Learning. He has led many research and design projects in science, mathematics, engineering, technology, and writing education. His current research interests include STEM reasoning (particularly studying practicing scientists and engineers) and learning (developing and studying integrations of science & engineering or science & math), neuroscience of complex learning (in science and math), peer interaction and instruction (especially for writing instruction), and engagement and learning (especially in science). He is a Fellow of several scientific societies (AAAS, APA, APS) as well as a Fellow and Executive member of the International Society for Design & Development in Education. He has served on two National Academy of Engineering committees, K12 Engineering Education and K-12 Engineering Education Standards.

**Chandralekha Singh** is a professor in the Department of Physics and Astronomy and the Director of the Discipline-based Science Education Research Center at the University of Pittsburgh. She obtained her PhD in theoretical condensed matter physics from the University of California Santa Barbara and was a postdoctoral fellow at the University of Illinois Urbana Champaign, before joining the University of Pittsburgh. She has been conducting research in physics education for more than two decades. She was elected to the Presidential-line of the American Association of Physics Teachers and is currently serving as the President. She held the Chair-line of the American Physical Society Forum on Education from 2009–2013 and was the chair of the editorial board of Physical Review Special Topics Physics Education Research from 2010–2013. She was the co-organizer of the first and third conferences on graduate education in physics and chaired the second conference on graduate education in physics in 2013. She is a Fellow of the American Physical Society, American Association of Physics Teachers and the American Association for the Advancement of Science.