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Examining Gender Differences in a Mechanical Engineering and Materials Science Curriculum*

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Women are severely underrepresented in many engineering majors, e.g., Mechanical Engineering and Materials Science (MEMS). Here, we investigate gender differences in the predictive relationship between students' high school GPA and foundational mathematics, science, and engineering courses in the first two years of an undergraduate MEMS curriculum using ten years of institutional data. We use multi-group Structural Equation Modeling to analyze the strength of these predictive relationships and gender differences both in these relationships and in course grades. We find a strong predictive pathway from high school GPA to overall first-year performance to advanced mathematics courses and finally to second-year MEMS courses. Further, women's higher average high school GPA than men is consistent with higher grades in all first-year courses except physics. The underperformance of women majoring in MEMS in physics compared to what is predicted based upon their high school GPA may be a sign of inequitable and non-inclusive learning environment in physics courses and is consistent with the low self-efficacy of women in physics throughout their engineering major in our prior research. These findings can be useful in engaging physics departments to focus on equity and inclusion and devise strategies to improve the learning environment so that female engineering students do not underperform compared to what is predicted based upon their high school GPA.

Keywords: gender, equity; inclusion; structural equation modeling; engineering education

1. Introduction and Theoretical Framework

Engineering schools are increasingly recognizing the importance of evidence-based approaches to improve student learning to ensure that all students have sufficient opportunities to excel regardless of their background [1–20]. Holistic consideration of how these engineering programs are currently succeeding in supporting their undergraduate majors is crucial in order to make appropriate changes to the curricula and pedagogies based upon metrics informed by data and ensure that all students are adequately supported. Data analytics can provide valuable information that can be useful in making informed decisions and transforming learning for all students including those from different demographics, e.g., based upon gender and ethnicity [21, 22].

Information obtained from data analytics on large institutional data in these areas can be an important component of understanding the role that foundational courses, e.g., in math and science, play in later engineering performance and determining whether there are gender differences in course performance or course relationships. Such results can aid in contemplating strategies for improving student support and ensuring that learning environments are equitable and inclusive so that all students can thrive. For example, if the institutional data suggest that women in engineering are performing worse than men in different courses compared to what is predicted based upon their high school GPA, it may signify inequitable and non-inclusive learning environment in those courses. In order to improve diversity in engineering, it is important that engineering schools take a careful look at the extent to which their programs for the majors are equitable and inclusive and provide adequate support to all students, especially for groups that are historically underrepresented in STEM, namely women and students from diverse ethnic and racial backgrounds [23, 24].

There is much prior research showing how gender differences in academic performance and career decisions of engineering students can result from biases and stereotypes [2, 25–31]. Many interrelated factors influence women's decision to pursue an education in engineering as well as subsequent decisions about which engineering major to study and even whether to remain in engineering [15, 32–36]. These factors include socio-cultural factors, motivational factors, and various aspects of prior education such as quality of teaching [17, 33, 34, 37–43]. In particular, it has been proposed that cultural bias and stereotypes can negatively impact the self-efficacy and academic performance of women in various STEM subjects including mathematics and physics [17, 33, 42, 43]. This is potentially damaging to prospective women

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in engineering since success in mathematics and science courses in high school has a positive impact on students' choice of and persistence in an engineering major [41, 44] and longer-term career goals [45, 46]. Further, success in first-year college STEM courses continues to provide feedback to engineering students and inform their motivational characteristics [47, 48].

Engineering programs often require students to complete a common first-year curriculum before beginning coursework for their chosen engineering major. This transition from first to second year when students choose their engineering major is critical, and in order to make decisions about the engineering curriculum overall, especially the extent to which it provides similar support to male and female engineering students prior to choosing an engineering major, it is important to study how students progress through the first-year curriculum and the extent to which performance in these foundational courses predicts performance in later courses, disaggregated by gender. Additionally, it is important to study gender differences in performance in these foundational courses and investigate the extent to which these gender differences could be at least in part explained by prior preparation. If certain courses show gender differences which cannot be explained by prior preparation, those courses could be investigated in depth to identify what could cause the disparity and design a course which promotes learning for all students in an equitable learning environment.

Our conceptualization of equity in learning includes three pillars: equitable access and opportunity to learn the content, equitable and inclusive learning environment, and equitable outcomes. Thus, by equity in learning, we mean that not only should all students have equitable opportunities and access to resources, they should also have an equitable and inclusive learning environment with appropriate support and mentoring so that they can engage in learning in a meaningful and enjoyable manner and the learning outcomes should be equitable. By equitable learning outcomes, we mean that students from all demographic groups (e.g., regardless of their gender identity or race/ethnicity) who have the pre-requisites to enroll in courses have comparable learning outcomes. This conceptualization of equitable outcome is consistent with Rodrigues et. al.'s equity of parity model [49]. The learning outcomes include student performance in courses as well as evolution in their motivational beliefs such as self-efficacy etc. because regardless of performance, students' motivational beliefs can influence their short and long-term retention in their major and careers. In other words, an equitable and inclusive learning environment should provide guidance, support and mentoring to all students as appropriate and ensure that students from all demographic groups have equal sense-of-belonging regardless of their prior preparation so long as they have the prerequisite basic knowledge and skills. An equitable and inclusive learning environment would also ensure that students from all demographic groups and prior preparation embrace challenges as learning opportunity instead of being threatened by them and enjoy learning. Equitable learning outcomes also include the ability of the courses to empower students from all demographic groups and make them passionate to pursue further learning and careers in related areas. We note that equitable access and opportunity to learn, equitable and inclusive learning environment and equitable outcomes are strongly entangled with each other. For example, if the learning environment is not equitable and inclusive in a particular course, the learning outcomes are unlikely to be equitable.

Here, we report a study which harnesses data analytics applied to 10 years of institutional data for Mechanical Engineering and Materials Science (MEMS) majors at a large state-related university to investigate how well the performance of MEMS majors in early foundational courses predicts performance in subsequent engineering courses. The MEMS curriculum was chosen for this investigation because the foundational courses in mathematics, physics, and chemistry are likely to be very important for these students to excel in their studies. The MEMS curriculum is also ideal to explore since mechanical engineering is the engineering program with the largest number of students at the studied university. We note that materials science undergraduate majors, though very few in number at the studied university, are also included in this analysis since they take the same courses considered in this study as mechanical engineering majors through the first two years. These courses for the majors have been offered for decades under the assumption that the later courses would build on the earlier ones coherently to help the majors build a robust knowledge structure and develop their problem solving, reasoning, and meta-cognitive skills. Investigating the predictive relationships between these courses will not only allow us to measure how well the courses in the curriculum build upon one another, but will also provide a structure in which we can test for gender differences throughout the model, both in grades earned and the strength of the relationships between courses.

This investigation can be useful for other institutions who may perform similar analyses in order to contemplate strategies for improving education in different engineering programs in a holistic manner as well as improving equity and inclusion. In particular, institutions could compare their findings with the 10-year baseline data provided here from a large US-based public university for the synergy observed between courses in a mechanical engineering curriculum, gender differences throughout the curriculum, or use this analysis as a template for similar analyses of other engineering curricula.

2. Research Questions

Our research questions regarding the curriculum for MEMS majors at a large state-related university are as follows.

RQ1. Are there *gender* differences in course performance among MEMS majors in first-year foundational courses and second-year courses for the major?
RQ2. Does performance in first-year foundational courses and advanced mathematics courses predict performance in second-year MEMS courses?
RQ3. Does the degree to which earlier course grades predict later course grades differ for men and women?

We note that if there are gender differences, we focus on whether the observed trends could potentially signify lack of equitable and inclusive practices in learning environment in certain courses.

3. Methodology

3.1 Measures

Using the Carnegie classification system, 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 and reasonably selective with low transfer-in from other institutions [50]. De-identified data were provided by the university on all engineering students who had enrolled in introductory courses from Fall 2009 through Spring 2019. The data include demographic information such as gender, which is central to this study. We note that gender is not a binary construct. However, the university data includes "gender" as a binary categorical variable. Therefore, that is how the data regarding gender are represented in these analyses. From the full sample of undergraduate engineering majors, a sub-sample was obtained by applying several selection criteria to select out MEMS majors from other engineering majors who took some MEMS courses listed in Table 1 (e.g., bioengineering, chemical engineering, and industrial engineering students all also take Mechanics 1). In particular, in order to be kept in the sample, students were required to meet the following criteria: (1) enroll in at least one of the two introductory engineering courses listed in Table 1, row (2) enroll in Mechanics 2. Note that all of the courses we consider in this analysis in Table 1 are required courses in the curriculum for MEMS majors. After applying the selection criteria, the sample contains 1485 students. The students in the sample are 16.4% female and had the following race/ethnicities: 82.9% White, 7.2% Asian, 3.8% African American, 2.2% Latinx, and 3.8% Other or Unspecified.

The data also include high school GPA on a weighted 0–5 scale that includes adjustments to the standard 0–4 scale for Advanced Placement and International Baccalaureate courses. Finally, the data include the grade points and letter grades earned by students in each course taken at the university. Grade points are on a 0–4 scale with A

Table 1. All required first-year courses along with second-year mathematics and selected MEMS courses are listed. Full course names are given along with shortened names used elsewhere in this paper and the terms in which the courses are typically taken by MEMS majors

Term	Full course name	Short name
1	General Chemistry for Engineers 1	Chem 1
	Intro to Engineering Analysis	Engr 1
	Basic Physics for Science and Engineering 1	Phys 1
	Analytic Geometry and Calculus 1	Calc 1
2	General Chemistry for Engineers 2	Chem 2
	Intro to Engineering Computing	Engr 2
	Basic Physics for Science and Engineering 2	Phys 2
	Analytic Geometry and Calculus 2	Calc 2
3	Analytic Geometry and Calculus 3	Calc 3
	Intro to Matrices and Linear Algebra	Linear Algebra
	Materials Structure and Properties	Materials Structure
	Statics and Mechanics of Materials 1	Mechanics 1
4	Differential Equations	Diff Eq
	Statics and Mechanics of Materials 2	Mechanics 2

= 4, B = 3, C = 2, D = 1, F = 0, where the suffixes "+" and "–" respectively add or subtract 0.25 grade points (e.g., B– = 2.75), with the exception of A+ which is reported as the maximum 4 grade points.

3.2 Analysis

In order to evaluate the grades that MEMS majors earn in their courses by gender, we grouped students by the gender variable and computed standard descriptive statistics (mean, standard deviation, sample size) separately for each group [51]. Gender differences in course grades were evaluated using Cohen's d to measure the effect size [52, 53], as is common in education research [54].

The extent to which the performance (i.e., grades earned) in earlier foundational courses predicts performance in later MEMS courses was evaluated using Structural Equation Modeling (SEM) [55]. In the past we have investigated the overall relationships between courses in this engineering curriculum using multiple linear regression [56]. Here, we extend this research by using SEM in order to cluster together courses in sequences before analyzing predictive relationships and, using multi-group SEM, test for gender differences among engineering majors.

SEM is the union of two statistical modeling techniques, namely Confirmatory Factor Analysis (CFA) and Path Analysis [55]. The CFA portion tests a model in which observed variables (or "indicators") are grouped into latent variables (or "factors"), constructed variables that represent the variance shared among all indicators that load on a particular factor [55]. The strength of the relationship between indicators and factors is measured by the factor loading, λ. Further, one of the unstandardized factor loadings per factor is fixed to $\lambda = 1$ in order to define the units and scale of the factor itself [55]. The factor loadings of other indicators are measured relative to this fixed factor loading [55]. The degree to which each indicator is explained by the factor is measured by standardizing the factor loadings, to $0 \leq \lambda \leq 1$, where λ^2 gives the percentage of variance in the indicator explained by the factor [55].

The Path Analysis portion then tests for the statistical significance and strength of regression paths between these factors, simultaneously estimating all regression coefficients, β, throughout the model [55]. This is an improvement over a multiple linear regression model in which only a single response (target or outcome) variable can be predicted at a time, which problematically disallows hierarchical structures [57]. By estimating all regression paths simultaneously, all estimates are able to be standardized simultaneously, allowing for direct comparison between standardized β coefficients throughout the model. In these models, we further estimate the intercepts (i.e., the mean when controlling for all predictors) of all indicators and factors. Indicator intercepts are denoted by τ and factor intercepts by α.

In this paper, we report the model fit for SEM using the Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), and Root Mean Square Error of Approximation (RMSEA) [55, 58]. Commonly cited standards for goodness of fit using these indices are as follows: For CFI and TLI, Hu and Bentler [58] found that many authors [58–60] suggest values above 0.90 and 0.95 indicate a good fit and a great fit, respectively. For RMSEA, several authors [58, 61] suggest that values below 0.10, 0.08, and 0.05 indicate a mediocre, good, and great fit, respectively.

Finally, these model estimations can be performed separately for different groups of students (e.g., men and women) using multi-group SEM. These differences are measured in a series of tests corresponding to different levels of "measurement invariance" in the model, with each step fixing different elements of the model to equality across the groups and comparing to the previous step via a Likelihood Ratio Test (LRT) [55]. A non-significant p-value at each step indicates that the estimates are not statistically significantly different across groups. "Weak" measurement invariance is demonstrated by fixing the factor loadings to equality, "strong" invariance is demonstrated by further fixing to equality the indicator intercepts, and finally "strict" invariance is demonstrated by further fixing to equality the residual error variance of the indicators. If measurement invariance holds at least through "strong" invariance, then all remaining differences between the groups occur at the factor level, either as differences in factor intercepts or β coefficients [55]. If instead measurement invariance does not hold, then the equality constraint on estimates (especially factor loadings and indicator intercepts) between groups can be relaxed for one estimate at a time in order to find the set of estimates for which partial measurement invariance holds. That is, the equality constraint can still be imposed on a subset of the factor loadings, intercepts, and/or residual variances, with the remaining estimates allowed to differ between groups.

Using SEM, we model student progression through the second year of the MEMS curriculum by grouping courses together into factors by their subject (e.g., introductory physics or advanced mathematics). Further, we found that all courses taken in the first year covary to such a degree that an overall first-year factor that loads on each of the first-year subject factors produces the best model fit. We use multi-group SEM to test for gender moderation, i.e., to test for gender differences in the predictive relationships in the model, as well as mean differences in course grades (indicators) and course factors [55].

Due to the nature of institutional grade data, modeling students' progress through an entire curriculum involves a large amount of missing data due to various reasons. These can include students receiving credit for courses taken elsewhere (e.g., over the summer at a different college), not completing the curriculum, skipping courses that are normally required with special permission, and the inevitable errors that occur in large datasets. The default approach to missing data in many modeling programs, listwise deletion, is then not desirable since it leaves very few students in the sample and can bias the results [62]. Considering this, we employed Full Information Maximum Likelihood (FIML) in order to impute missing data within the SEM model [55].

In addition to the aforementioned benefits of using SEM such as simultaneous estimation of all model elements and the ability to use FIML for missing data estimation, the basic structure of SEM also provides benefits to the modeling process. In particular, by first using CFA to group indicators into factors and then performing path analysis on those factors, the effect of measurement error is minimized since the error variance will be left at the indicator level and does not contribute to the estimation of regression coefficients at the factor level [55].

All analyses were conducted using R [63], making use of the package lavaan [64] for the SEM analysis and the package tidyverse [65] for data manipulation and descriptive statistics.

4. Results

RQ1: Gender Differences in Course Performance

In order to investigate for gender differences in course grades and answer **RQ1**, we grouped students by the gender variable and first calculated the standardized mean difference, Cohen's *d*, to measure the effect size of the gender differences [52, 53]. Table 2 shows these results for all MEMS students who at least continued through Mechanics 2 (typically taken in the fourth term). Note that since enrollment in Mechanics 2 was used as a selection criterion, the population in every other course is less than that in Mechanics 2, since students may be missing grades for previous courses for a variety of reasons. We find that, on average, women performed similar to or slightly better than men in all courses except introductory physics (Physics 1 and 2). This general pattern matches that of high school GPA, though the effect sizes of the gender differences in the courses is small, with the highest difference occurring in Linear Algebra a small effect size (d = 0.24), and a medium effect size in high school GPA (d = 0.47). Though still small in effect size, the gender differences seen in introductory physics are the only ones in which men earn higher grades on average, despite the same population showing women performing better than men in high school GPA and grades in other courses.

Looking at the patterns of gender differences in Table 2 by subject shows that in the second year (terms 3 and 4), this pattern of women earning higher grades than men is still present in advanced mathematics and is on par with the strongest gender differences observed in the first year. On the other hand, in their MEMS courses, men and women are earning more similar grades, except women earning slightly higher grades in Mechanics 1.

The full grade distributions as described on average in Table 2 are shown in Fig. 1 (first-year courses) and Fig. 2 (second-year courses). In these distributions, we can see that in most courses, especially the second year courses in Fig. 2, women earn A and A+ grades at a slightly higher rate than men, who in turn have a slightly higher rate in earning lower grades. As noted in the preceding discussion of Table 2, physics was the only subject with appreciable grade differences favoring men, and that can be seen again in Fig. 1, with men earning higher rates of grades B+ and higher, and women earning higher rates of B grades and lower.

In some courses where we saw very little mean gender differences in Table 2, we can still observe some interesting grade distributions. For example, Calculus 2 in Fig. 1 has an alternating pattern of men and women earning higher rates of the various letter grades. Further, the course with the gender difference closest to that of high school GPA, namely Linear Algebra in Table 2, has a noticeably large rate of A grades earned by both men and women, but especially large for women. This may be because Linear Algebra is the only course in the MEMS curriculum that has been consistently taught by a female professor, and this could have an impact on female students' performance. However, we do not have adequate data to investigate the in detail the impact of the gender of the instructor. Finally, the courses in both Figs. 1 and 2 display a general trend of peaks of varying sizes at A, B, and C grades with the exception of Engineering 1, which shows an especially high mean with a single peak at A.

RQ2: Predictive Relationships Between Courses

Turning then to **RQ2**, we use SEM to test for the

Table 2. Descriptive statistics are reported for grades in courses taken by MEMS majors through the second year, on a 0-4 scale, and high school GPA on a weighted 0-5 scale. Only students who have taken Mechanics 2 are reported in order to restrict to MEMS majors. Reported are the sample size (N), mean grade points earned (μ), and standard deviation of grade points (σ) for men and women separately, along with Cohen's d measuring the effect size [52, 53] of the gender difference. $d < 0$ indicates the mean for men is higher, $d > 0$ indicates the mean for women is higher

Course	Gender	N	μ	σ	d
High School GPA	F	243	4.07	0.37	0.47
	M	1242	3.88	0.44	
Chemistry 1	F	191	2.76	0.80	0.09
	M	933	2.68	0.90	
Chemistry 2	F	185	2.67	0.82	0.19
	M	873	2.51	0.83	
Engineering 1	F	187	3.63	0.40	0.18
	M	937	3.55	0.45	
Engineering 2	F	197	3.28	0.65	–0.01
	M	978	3.28	0.65	
Physics 1	F	192	2.79	0.68	–0.15
	M	927	2.90	0.72	
Physics 2	F	201	2.67	0.73	–0.08
	M	1040	2.73	0.80	
Calculus 1	F	140	3.16	0.68	0.18
	M	719	3.03	0.70	
Calculus 2	F	170	2.90	0.84	0.01
	M	871	2.89	0.84	
Calculus 3	F	228	2.94	0.86	0.14
	M	1157	2.81	0.92	
Linear Algebra	F	222	3.26	0.79	0.24
	M	1184	3.06	0.88	
Diff Eq	F	235	3.01	0.83	0.19
	M	1204	2.84	0.95	
Materials Structure	F	220	2.92	0.89	0.01
	M	1204	2.92	0.93	
Mechanics 1	F	243	3.25	0.74	0.08
	M	1236	3.19	0.78	
Mechanics 2	F	243	2.94	0.95	0.00
	M	1242	2.94	1.03	

degree to which performance in earlier courses predicts that of later courses in the curriculum. The full 1485 student sample was used in all stages of SEM, with FIML employed to impute missing data [55]. We grouped first-year courses by their subject (Calculus, Chemistry, Engineering, and Physics), then further grouped these four subjects into a "First Year" factor. Second-year mathematics courses are grouped together into an "Advanced Math" factor, and MEMS courses are left ungrouped in order to separately predict the grades in each of these courses, as well as to allow the term 3 courses (Mechanics 1 and Materials Structure) to predict the term 4 course (Mechanics 2).

The final model is shown in Fig. 3 (CFI = 0.972, TLI = 0.968, RMSEA = 0.042, all indicating a great model fit [58–61]), in which non-significant regression paths have been trimmed from the model. Note that since there are gender differences present, all values shown are the unstandardized values, for which a majority of the factor loadings, intercepts, and regression coefficients have been fixed to equality [55]. The primary flow of predictive paths is such that each first year subject loads strongly on the overall First Year factor. This First Year factor then strongly predicts the Advanced Math factor, which in turn strongly predicts each of the MEMS courses. There are two smaller additional regression paths, with Chemistry predicting Materials Structure and Materials Structure predicting Mechanics 2, both over and above the primary predictive paths from Advanced Math.

RQ3: Gender Differences in the Structural Equation Model

To test for gender differences and answer **RQ3**, we used multi-group SEM to test for differences in the

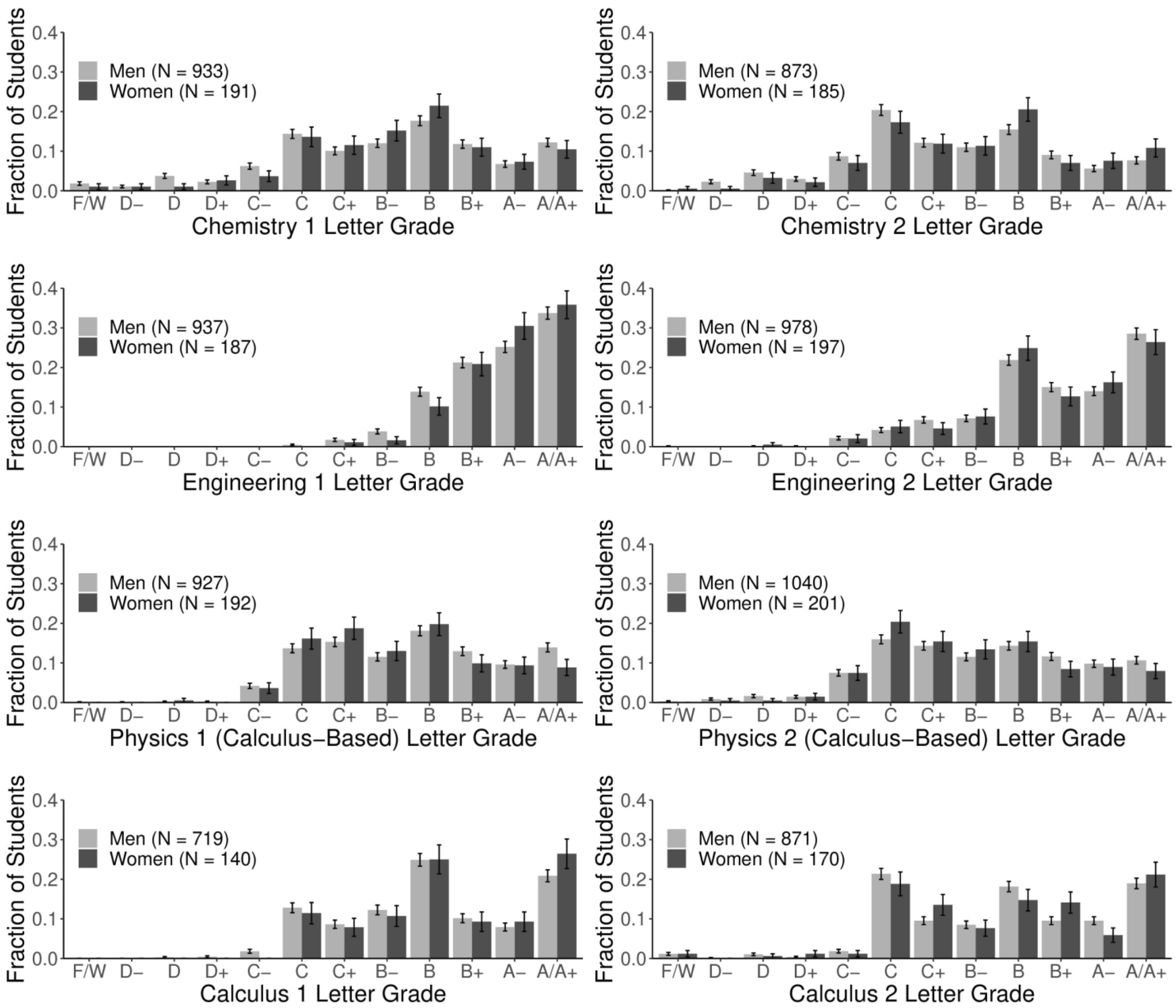

Fig. 1. Grade distributions of MEMS majors in first-year courses, plotted separately for men and women. The proportion of each gender group that earns each letter grade is plotted along with the standard error of a proportion [51].

model [55], first testing factor loadings, then indicator intercepts, then residual variances, and finally regression paths. The estimates that differed for men and women are reported in Fig. 3. In each step, the model fit was great, with CFI > 0.95, TLI > 0.95, and RMSEA < 0.05 [58–61]. We did not find full measurement invariance at either the factor loading ("weak") or item intercept ("strong") stages [55]. That is, when fixing all factor loadings to equality, the Likelihood Ratio Test (LRT) showed significant differences in the model with $p < 0.05$ unless some estimates were allowed to vary between men and women [55]. In particular, Fig. 3 shows that the factor loading (λ) of Physics on the First Year factor is slightly lower for women ($\lambda_F = 0.84$) than for men ($\lambda_M = 0.89$). Though seemingly a small difference, this gender difference in factor loading is sufficient to account for men's higher performance in physics courses overall (Table 2 and Fig. 1). Further, three courses showed differences in their intercepts (τ): Physics 1 ($\tau_F = 0.62$, $\tau_M = 0.71$), Engineering 2 ($\tau_F = 1.02$, $\tau_M = 1.16$), and Linear Algebra ($\tau_F = 0.63$, $\tau_M = 0.51$). Each of these indicates deviations from the course grade gender differences that would be predicted solely by the difference in high school GPA and, in the case of Physics 1, the aforementioned factor loading difference.

Notably, Fig. 3 shows that apart from the mean difference in high school GPA ($\tau_F = 4.07$, $\tau_M = 3.88$), there are no additional gender differences present in any regression paths leading to calculus, chemistry, or MEMS courses. This does not mean that the model predicts no gender differences in these courses. Rather, this means that the gender differences observed in these courses are consistent with the gender difference observed in high school GPA propagating through the model's predictive paths to each course. That is, the women MEMS majors are coming in with a higher high school

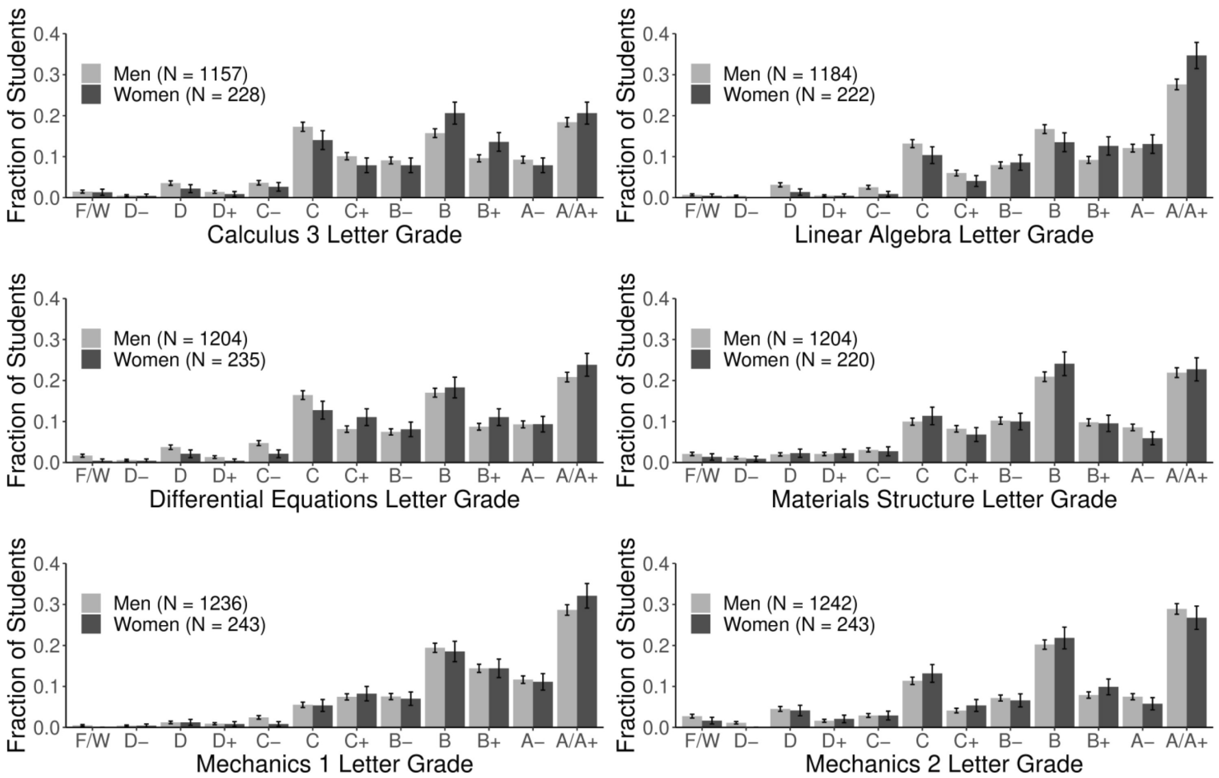

Fig. 2. Grade distributions of MEMS majors in second-year mathematics and engineering courses, plotted separately for men and women. The proportion of each gender group that earns each letter grade is plotted along with the standard error of a proportion [51].

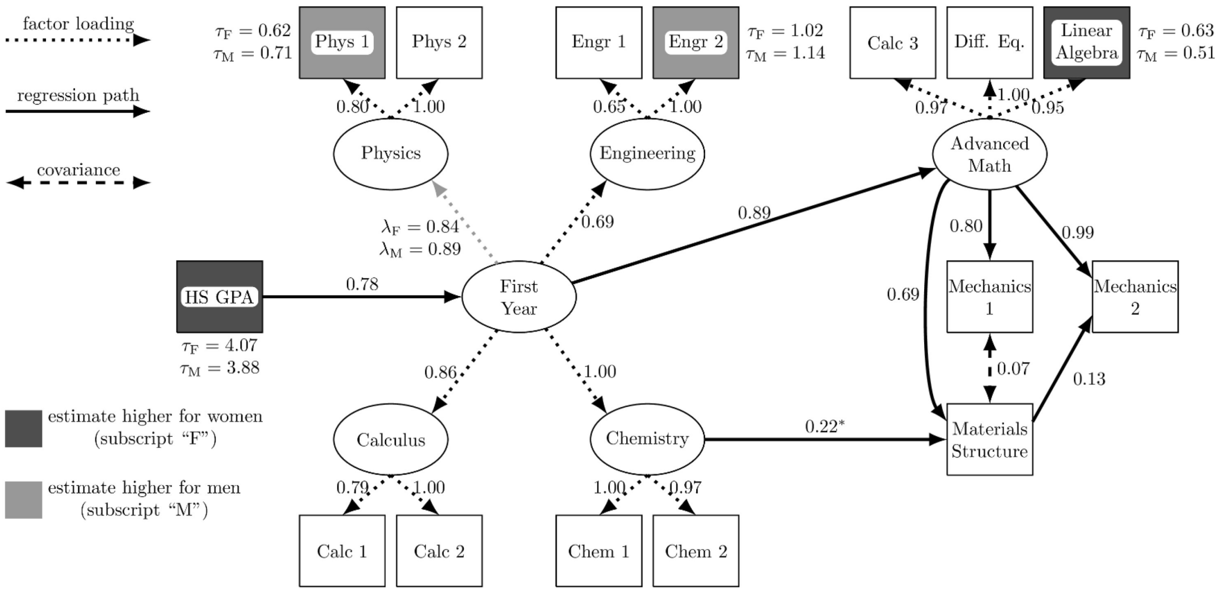

Fig. 3. A diagram of the SEM model designed to test for the relationships between courses in the MEMS curriculum, as well as gender differences therein. All 1485 students in the sample were included in the model, with FIML used to estimate missing data. Reported next to each line are the unstandardized values for factor loadings, regression coefficients, and covariances. Estimates that differ between female (subscript "F") and male (subscript "M") students are reported separately for each gender, in this model these are differences in intercepts (τ) and factor loadings (λ). High School GPA (HS GPA) and all first-year factors were allowed to regress on Advanced Math and the second-year engineering courses, but many paths were not statistically significant ($p < 0.05$) and thus are not shown. All drawn paths are significant to the $p < 0.001$ level except the one denoted with a superscript *, which is significant to the $p < 0.01$ level. All missing paths are not statistically significant, with $p > 0.05$. Line styles indicate the type of relationship between connected items, with factor loadings, regression paths, and covariances represented by dotted, solid, and dashed lines, respectively (please see legends on the left hand side for details).

GPA than men and earning higher grades than men in the majority of their courses consistent with that high school GPA difference. The exceptions to this occur only in four courses, with the largest departure from high school GPA occurring in the physics sequence, and especially in Physics 1 (in which the students learn mechanics).

5. Discussion

Our results indicate an overall pattern of strong cohesion through the first two years of this MEMS curriculum (Fig. 3). In particular, the strong predictive pathway from high school GPA to the First Year factor to the Advanced Math factor to each MEMS course shows a robust cohesion throughout this curriculum. Further, we see that the First Year factor itself is loaded on very strongly by each of the first-year courses, though notably least strongly by first-year engineering courses (which consists of a sequence focusing on introduction to programming for engineers and other engineering basics), perhaps due to the high grades overall and narrow grade distributions in those courses.

Turning to gender differences in these courses, we find that women tended to earn similar or slightly higher grades on average than men in most subjects. This pattern is consistent with their average high school GPA, where these same women have a higher GPA than the men. The only subject that does not fit this pattern is physics, in which, on average, the men are earning higher grades despite having a lower high school GPA and women earning higher grades in every other concurrent course. However, we find that in physics, instead of the gender gap merely diminishing relative to high school GPA similar to other college courses, women are now earning lower grades than men, inconsistent with high school GPA and all other course grades (where women always earn higher or comparable grades compared to men).

Testing these gender differences further using multi-group SEM provided further support for these interpretations. In nearly all courses, the gender differences in high school GPA were sufficient to predict course grade gender differences. In two individual courses there were small additional gender differences found, namely Engineering 2 in which women and men earned the same grades on average (and so the course-level gender difference slightly favors men controlling for high school GPA), and Linear Algebra in which women earn slightly higher grades than otherwise predicted. These single-course differences may simply be normal noise or may have an underlying cause (e.g., Linear Algebra having been taught by a female faculty member over the years when the data were collected), but neither fits a larger pattern. On the other hand, introductory physics shows a gender difference affecting both Physics 1 and Physics 2 (namely, the λ difference from the First Year factor to the Physics factor) in addition to an intercept difference in Physics 1.

With regards to what may be partly responsible for introductory physics standing out as having significant gender differences and what may be done to ameliorate the situation, our prior research on students' self-efficacy in these courses reveals a similar pattern where female students in introductory physics have significantly worse self-efficacy than male students even after controlling for performance [48]. The same is not true for other courses in the MEMS curriculum. Additionally, physics may be a field in which practitioners are more likely to believe that innate talent (i.e., "brilliance") is required for excelling in the field, which may have a disproportionate negative effect on the performance of women due to stereotype threat [70]. Since prior research has found a feedback loop between grades and self-efficacy [45, 66, 71–76] and grades play a key role in students' crucial decisions about whether to remain in college and which major to pursue [41, 44–46], it is important for physics departments to engage in serious efforts towards improving equity and inclusion in introductory physics courses, including interventions designed to boost students' self-efficacy, growth mindset and sense of belonging in physics [77–81]. While our research suggests that self-efficacy is related to students' grades in introductory physics, we note that these psychological factors of self-efficacy, growth mindset and a sense of belonging are interrelated [48, 49, 82–86], and any intervention intending to impact one of the factors could impact the others as well.

6. Conclusion and Future Research

In all of our gender analysis, the introductory physics sequence is standing out as a source of gender differences in this curriculum. This could be indicative of strong stereotype threats due to societal biases associated with physics as well as an inequitable or non-inclusive environment in these introductory physics courses that is disproportionately negatively affecting women. Future research can use what has been found here (the gender differences in Physics First Year Module Results) as an excellent starting point for a deeper investigation into the possible causes of this result, and more informed suggestions for future change. For example, one can examine in-depth the experiences of women taking these courses and how they perceive their physics courses as compared to other courses in the MEMS curriculum. For example, students could be asked how the courses are taught and assessed and whether there are any distinguishing features in the learning environment of physics which marks it differently from other MEMS courses. This could be done at several points in the MEMS curriculum and incorporate surveys and extended follow-up interviews.

We also note that our analysis focused on those students who, when entering the second-year, chose to major in a ''physics-heavy'' engineering major and still we observed these gender differences surrounding introductory physics. A future study could investigate whether the gender differences in course grades in introductory physics are even more pronounced among the students in less physics heavy engineering majors such as bioengineering, chemical engineering, or industrial engineering.

In conclusion, the underperformance of women majoring in MEMs in physics courses compared to what is predicted based upon their high school GPA may be a sign of inequitable and non-inclusive learning environment in physics courses and is consistent with the low self-efficacy of women in physics throughout their engineering major in our prior research. These findings can be useful in engaging physics departments to focus on equity and inclusion and devise strategies to improve the learning environment so that female engineering students do not underperform compared to what is predicted based upon their high school GPA.

In future, SEM will be used to evaluate the cohesiveness of a curriculum by examining the predictive relationships between course grades for students with different demographics backgrounds, including not only gender, but also their race and ethnicity, low socioeconomic status, and first-generation college status. Further, course grade differences can be evaluated at the same time across the full curriculum, and how later gender differences are explained by earlier gender differences in the curriculum. These studies can provide insight into the best practices to address such disparities and improve equity and inclusion in the learning environment.

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