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How Engineering Identity of First-Year Female and Male Engineering Majors is Predicted by Their Physics Self-Efficacy and Identity*

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Physics courses are important for engineering students because not only are they the foundation for many engineering courses, but students' physics motivational beliefs such as self-efficacy and identity may also influence their engineering identity as well as their choice of careers. In this study, we investigated first-year undergraduate engineering students' engineering identity and how it is predicted by their physics motivational beliefs (including physics self-efficacy, interest, perceived recognition and identity) in a calculus-based introductory physics course at a large research university in the US. We first investigated how these motivational beliefs change from the beginning to the end of the course (i.e., from pre to post) using descriptive statistics. Then, we investigated the predictive relationships among these motivational constructs using structural equation modeling (SEM). The SEM analysis revealed that students' engineering identity is predicted by their physics self-efficacy and identity. However, the descriptive statistics results showed that both male and female students' physics self-efficacy and identity decreased from pre to post, and female students' physics self-efficacy dropped even more than male students' did. Although students' average score on engineering identity also decreased from pre to post, this change was only statistically significant for male students. Our results show that students' physics perceived recognition is the strongest predictor of physics identity, and it also predicts students' engineering identity through physics identity and self-efficacy. We note that even though there were significant gender differences disadvantaging women in all motivational constructs studied, gender does not directly predict engineering and physics identities, which means that the gender differences in both identities are mediated through physics self-efficacy, interest and perceived recognition. Thus, in order to boost students' engineering identity, it is important to create an equitable and inclusive environment for learning physics, in which all students feel recognized and supported appropriately and develop a stronger physics and engineering identity.

Keywords: gender; self-efficacy; identity; perceived recognition; equity

1. Introduction and Theoretical Framework

Due to the increasing demand in the work force for engineers, many studies have focused on issues surrounding students' retention and persistence in engineering [1–7]. According to a recent report, the overall 4-year graduation rate of students in the US who enter an undergraduate engineering program remains below 40% in the last 10 years [8]. In particular, 20% of students are lost within the first year alone [8]. Another study shows that only 42% of seniors enrolled in undergraduate engineering programs definitely intend to pursue a career in engineering upon graduation [9]. Moreover, the retention issue is even more severe for students from underrepresented groups such as women [6, 8, 10]. Studies show that less than 30% of all engineering degrees are awarded to women [1], and women have been found to leave engineering at an earlier stage than men [11, 12]. Many factors have been shown to affect undergraduate students' choices to persist in engineering, for example, students' prior preparation, quality of teaching, sociocultural and motivational factors [3, 13–22]. In particular, motivational factors such as engineering identity have been shown to be significant indicators of students' retention in engineering, and also influence their short-term and long-term career goals [23–26].

In prior research, engineering identity has been studied from several different perspectives [27, 28]. For example, some studies consider engineering identity as the combination of multiple identities such as academic, social and occupational identities [24, 29, 30]. Some other studies identified several cognitive, affective, and performance variables to comprise engineering identity [4, 31–33]. Another widely used definition of engineering identity is how students see themselves with respect to engineering or whether they see themselves as an engineer based on their perceptions and navigation of engineering related experiences [34–36], which is also the most relevant definition to our study. However, studies have shown that many students have very few direct experiences with engineering before they enter college [37]. Thus, due to the interdisciplinary nature of engineering, students' experiences in

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other engineering related domains such as math and science may play a very important role in the development of students' engineering identity [32]. For example, studies have shown that doing well in math and science courses in high school has a positive impact on students' choice of and persistence in an engineering major and longer-term career goals [3, 5]. Therefore, studying students' motivational beliefs in engineering related domains, e.g., physics, and how they interact with engineering identity may help us develop a better understanding of students' attrition and retention in engineering majors.

Introductory physics courses usually serve as a prerequisite for many engineering courses, and thus for most students who enrolled in an undergraduate engineering program, physics is mandatory in their first year. A study shows that students' grades in introductory physics courses predict their performance in later engineering courses [38]. Moreover, physics is not only important for engineering students' knowledge building but may also affect their attitudes and self-beliefs about being an engineer. For example, studies have shown that students' physics motivational beliefs such as self-efficacy and interest can influence their engineering career agency [39]. However, physics is also one of the most stereotyped domains in the sense that it is a traditionally male-dominated field and has a masculine culture and a masculine public image [13, 19]. In addition, physics is perceived by many people to depend largely on the innate qualities of "brilliance" or "genius", which are also typically attributed to men [40–42]. These societal stereotypes not only impact female students' physics motivational beliefs but may also dissuade them from pursuing study in physics-related disciplines such as engineering. A prior study shows that in an undergraduate engineering program, students' self-efficacy in physics showed a larger gender difference than their self-efficacy in mathematics, engineering, and chemistry [43]. In addition, physics was the only science subject for which female engineering students had a lower average score than male engineering students [43, 44]. Therefore, the gender difference in physics motivational beliefs may partially explain the underrepresentation of women in engineering disciplines and studying the relationship between students' physics and engineering motivational beliefs may provide new insights into how to improve the recruitment, retention and diversity within engineering.

In this study, we investigated first-year undergraduate engineering students' engineering identity and physics motivational beliefs (including physics identity, self-efficacy, interest and perceived recognition) in a calculus-based introductory physics course. In particular, we focus on how students' motivational beliefs in physics and engineering change from the beginning to the end of the course and the predictive relationships among these motivational constructs. This course is usually taken by engineering students in the first semester of their first-year of undergraduate study, and they must pass this course before they declare a specific major, e.g., electrical engineering, within the engineering school. Thus, students' experiences in this course are not only important for the development of their physics and engineering motivational beliefs but may also influence their choice of majors. Even though there are several studies focusing on students' physics and engineering motivational beliefs [31, 32, 39], very few studies have investigated how male and female students' engineering identity and physics motivational beliefs change in an introductory physics course, and how students' physics motivational beliefs predict their engineering identity at the end of the course.

As noted, students' identity in engineering or physics is related to whether they see themselves as an engineer or a physics person, and these identities have been shown to influence students' career decisions and outcome expectations [4, 34, 45, 46]. The other three motivational beliefs considered in this study (physics self-efficacy, interest and perceived recognition) have been shown to be the predictors of students' physics identity and also very important to students' engagement, performance and retention [46–50]. In particular, self-efficacy is defined as students' beliefs in their capability to succeed in a certain situation, task, or particular domain [47, 51, 52]. Studies suggest that students with high self-efficacy in a domain often enroll in more challenging courses in that domain than those with low self-efficacy because they perceive difficult tasks as challenges rather than threats [53–55]. Another motivational belief is interest, which is defined by positive emotions accompanied by curiosity and engagement in a particular topic [56]. Interest has also been shown to influence students' learning [53, 56, 57]. For example, one study suggested that making science courses more relevant to students' lives and transforming curricula to promote interest in learning can improve students' achievement [58]. Perceived recognition (also called external identity) in physics refers to students' perception about whether other people see them as a physics person [59]. Some quantitative studies focusing on the relation between students' physics identity and other motivational beliefs show that physics perceived recognition is actually the strongest predictor of physics identity as compared to physics interest and self-efficacy [39, 47].

In this study, we first investigated how students' engineering and physics motivational beliefs change from the beginning to the end of the introductory physics course (i.e., from pre to post) using descriptive statistics. Then, we performed structural equation modeling (SEM) using the post data to study the predictive relationships among these motivational constructs. We focus on the predictive relationships at the end of the course because most students take this course in the first semester in college, and they may feel uncertainty and anxiety during the transition from high school to college. Thus, students' motivational beliefs may be more stable after they have been on campus for a semester. In addition, since students' perceived recognition is related to their interaction with TAs and instructors, only after the course can students answer these survey questions based on their real experience in the course. We adapt the physics identity model from Hazari et al.'s (with Godwin, Lock, and Potvin) [39, 60, 61] and Kalender et al.'s prior work [47] as shown in Fig. 1, in which students' physics identity is predicted by their interest, recognition, and performance/competence or competency belief, which is very closely tied to self-efficacy. In this study, we add the engineering identity construct and focus on how students' physics motivational beliefs predict their engineering identity. As shown in Fig. 2 (a), we first considered a model (Model 1) in which there are only covariances between each pair of perceived recognition (Recog), self-efficacy (SE) and interest, so this model does not make assumptions about predictive relationships between these three mediating constructs. Then we considered another model (Model 2) in which perceived recognition is the predictor of both self-efficacy and interest (Fig. 2(b)), which is similar to the model in Kalender et al.'s prior work, in which competency belief and interest are predicted by perceived recognition (see Fig. 1(b)) [47].

2. Research Questions

Our research questions to investigate the relationship between physics motivational beliefs and engineering identity of undergraduate engineering students in the calculus-based introductory physics 1 course at a large research university in the US are as follows:

RQ1. How do male and female students' engineering identity and physics motivational beliefs (including physics identity, self-efficacy, interest, and perceived recognition) change from the beginning to the end of the course (i.e., from pre to post)?

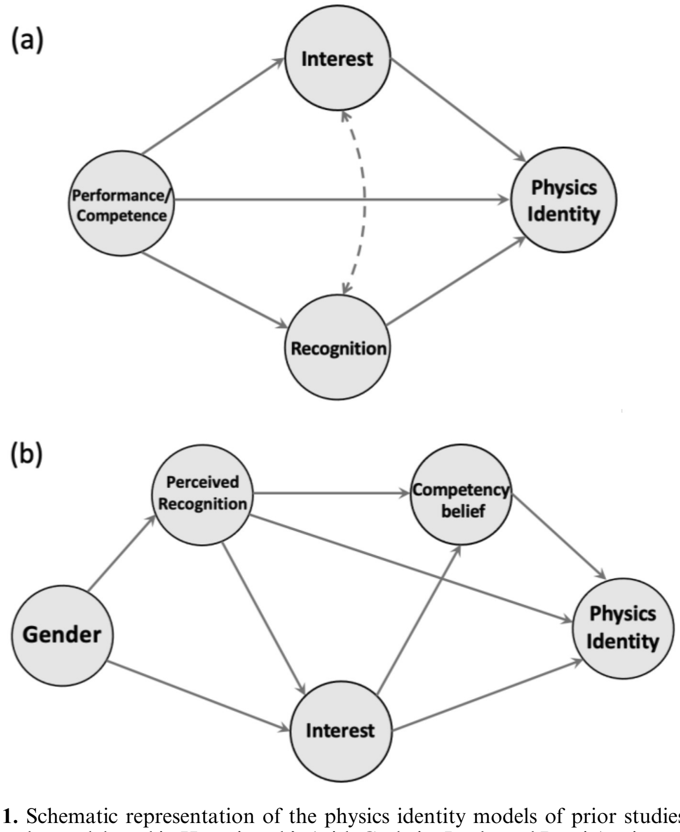

Fig. 1. Schematic representation of the physics identity models of prior studies. (a) shows the model used in Hazari et al.'s (with Godwin, Lock, and Potvin) prior studies [39, 60, 61] (b) shows the model used in Kalender et al.'s prior study [47].

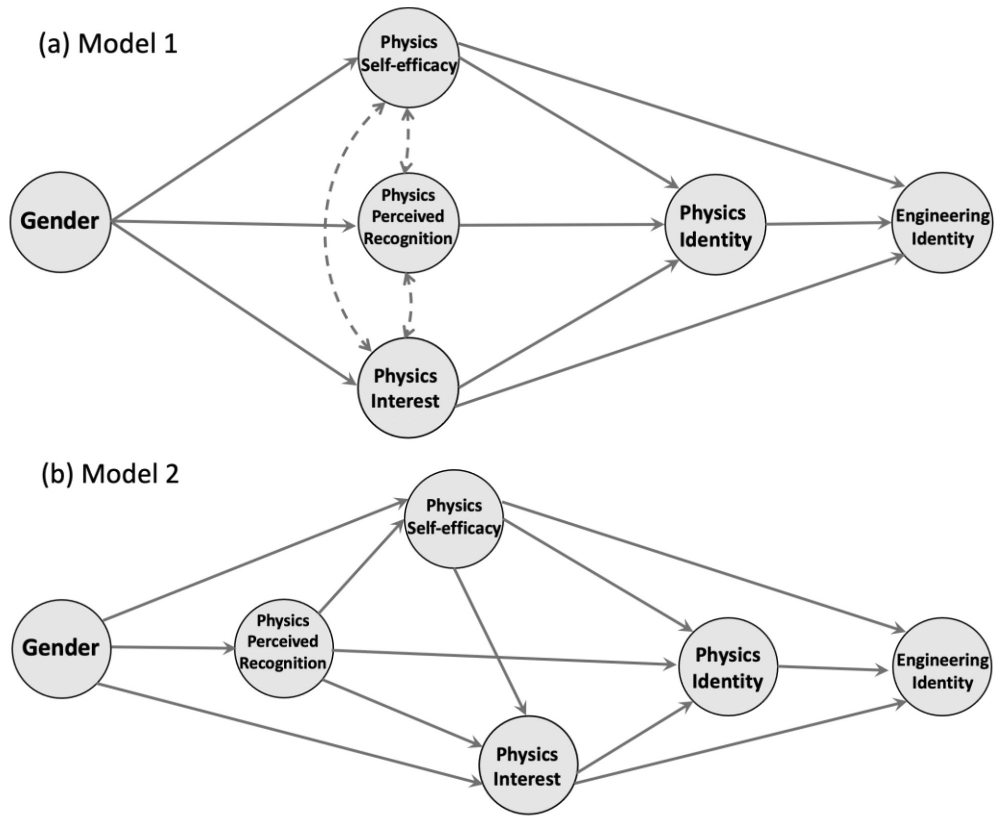

Fig. 2. Schematic representation of the path analysis part of the SEM models that shows how the relationship between gender and engineering identity is mediated by physics self-efficacy, physics perceived recognition, physics interest and physics identity. (a) In Model 1, physics self-efficacy, perceived recognition and interest are correlated with each other. (b) In Model 2, physics perceived recognition predicts physics self-efficacy and interest, and physics self-efficacy predicts physics interest. The direct paths from gender to physics and engineering identity are not shown because they are not statistically significant in both models.

RQ2. Are there gender differences in students' motivational beliefs and do they change from pre to post?

RQ3. How do students' physics motivational beliefs directly and indirectly predict their engineering identity?

3. Methodology

3.1 Participants

The motivational survey data used in this study were collected at the beginning and end of the semester from engineering students who took the calculus-based introductory physics 1 course at a large research university in the US. The data were collected from two consecutive fall semesters. The majority of these students were in the first semester of their first year in the undergraduate engineering program. This course consists of traditional lectures (4 hours per week) and recitations (1 hour per week), in which students typically work collaboratively on physics problems. The paper surveys were handed out and collected by TAs in the first and last recitation class of a semester. We named the data collected at the beginning of the semester as pre-data and that collected at the end of the semester as post-data. Finally, we combined the two semesters' data and put them into two categories, pre and post. The demographic data of students – such as gender – were provided by the university. Students' names and IDs were de-identified by an honest broker who generated a unique new ID for each student (which connected students' survey responses with their demographic information). Thus, researchers could analyze students' data without having access to students' identifying information.

In this study, we first investigated how students' physics and engineering motivational beliefs change from pre to post. However, because some motivational constructs were added to our survey at the end of the course in the first year of study, we do not have the pre-data for these constructs in that year. Thus, we first focus on 346 undergraduate engineering students (205 male students and 141 female students) who completed both the pre- and post-survey in the second year of study. We use Structural Equation Modeling (SEM) to study the predictive relationships among the motivational constructs at the end of the course [62]. Since we have complete post-data for both years of study, we performed SEM with the post-data collected from 761 engineering students (273 female students and 488 male students) in both years, which further improved the statistical power. Because students' gender information was obtained from the university, which offered binary options, we did the analysis with the binary gender data in this study.

3.2 Survey Instruments

In this study, we considered five motivational constructs – engineering identity and physics identity as well as physics self-efficacy, interest and perceived recognition. The survey items for each construct are listed in Table 1. The survey items were adapted from the existing motivational research [63–68] and have been revalidated in our prior work [69–75]. The validation and refinement of the survey involved use of one-on-one interviews with students using a think-aloud protocol, exploratory and confirmatory factor analyses (EFA and CFA) [76], Pearson correlation between different constructs and Cronbach's alpha (which is a measure of the internal consistency of each construct with several items) [77–79].

In our survey, each item was scored on a 4-point Likert scale (1–4). Students were given a score from 1 to 4 with higher scores indicating greater levels of motivational beliefs. Physics self-efficacy represents students' belief about whether they can excel in physics. We had four items for physics self-efficacy and these items had the response scale "NO!, no, yes, YES!" (Cronbach's α = 0.81), which have been shown to have good psychometric properties and a low cognitive load while reading [52, 64]. We also had four items for physics interest (Cronbach's α = 0.82). The question "I wonder about how physics works" had temporal response options "Never, Once a month, Once a week, Every day", whereas the question "In general, I find physics" had response options "very boring, boring, interesting, very interesting". The remaining two items under physics interest were answered on the "NO!, no, yes, YES!" scale. Physics perceived recognition corresponds to whether a student thinks other people see them as a physics person [46, 80, 81], and it includes three items which correspond to family, friends and TA/instructor (Cronbach's α = 0.87). Physics identity corresponds to students' belief about whether they designate themselves as a physics person [46]. Engineering identity corresponds to whether they see themselves as an engineer [34, 35]. The items for physics perceived recognition and both physics and engineering identity involved a four-point Likert response on the scale "strongly disagree, disagree, agree, and strongly agree" and they correspond to 1 to 4 points [82].

3.3 Quantitative Analysis of Survey Data

We calculated the mean score for each motivational construct for each student. Then, we used a *t*-test to compare students' pre- and post-scores for each motivational construct as well as conducted an

Table 1. Survey questions for each of the motivational constructs, along with factor loadings of CFA using two years of post-data. Lambda (factor loading) represents the correlation between each item and its corresponding construct, and the square of Lambda for each item gives the fraction of its variance explained by the construct.

Construct and Item	Lambda
Engineering identity	
I see myself as an engineer.	1.000
Physics identity	
I see myself as a physics person.	1.000
Physics self-efficacy (Cronbach's α = 0.81)	
I am able to help my classmates with physics in the laboratory or in recitation.	0.731
I understand concepts I have studied in physics.	0.736
If I study, I will do well on a physics test.	0.742
If I encounter a setback in a physics exam, I can overcome it.	0.682
Physics interest (Cronbach's α = 0.82)	
I wonder about how physics works †	0.650
In general, I find physics ‡	0.781
I want to know everything I can about physics.	0.791
I am curious about recent physics discoveries.	0.707
Physics perceived recognition (Cronbach's α = 0.87)	
My family sees me as a physics person.	0.913
My friends see me as a physics person.	0.909
My physics TA and/or instructor sees me as a physics person.	0.692

All Lambdas shown in this table are statistically significant with p value <0.001.
† The response options for this question are "Never, Once a month, Once a week, Every day".
‡ The response options for this question are "very boring, boring, interesting, very interesting".

analysis of gender differences using descriptive statistics. We performed Item Response Theory (IRT) analysis using the R software package "mirt" to check the response option distances for our survey constructs [83–86]. The results show that our scales had approximately equal distance between the levels, so the linearity assumption is reasonable and allowed us to calculate the traditional mean scores [83, 86]. Furthermore, we estimated the IRT-based scores (which tend to produce trait estimates that are linearly related to the underlying trait being measured) for each construct, and the results are highly correlated with the mean scores (the correlation coefficients are > 0.98 for all constructs), which indicates that the use of mean scores is reasonable [83].

Next, we performed Structural Equation Modeling (SEM) [62] with the post-data to study the predictive relationships between students' physics motivational beliefs and engineering identity. The SEM includes two parts: confirmatory factor analysis (CFA) and path analysis. In CFA, the model fit is good if the fit parameters are above threshold. In particular, Comparative Fit Index (CFI) > 0.9, Tucker-Lewis Index (TLI) > 0.9, Root Mean Square Error of Approximation (RMSEA) < 0.08 and Standardized Root Mean Square Residual (SRMR) < 0.08 are considered as acceptable and RMSEA < 0.06 and SRMA < 0.06 are considered as a good fit [77]. In our study, CFI = 0.976, TLI = 0.967, RMSEA = 0.054 and SRMR = 0.033, which represent a good fit. Thus, there is additional quantitative support for dividing the constructs as proposed. Besides, as shown in Table 1, all factor loadings are higher than 0.5, which is considered acceptable, and most of them are higher than 0.7. This means that the constructs extract sufficient variance from the observed variables, which allows us to perform the path analysis part of SEM [87].

Before performing the path analysis, we calculated the Pearson correlation coefficients pairwise between the motivational constructs. As shown in Table 2, all correlation coefficients are above 0.2, and most of them are less than 0.8, which means that even though these motivational constructs have strong correlations with each other, the correlations are not so high that they could not be examined as separate constructs in SEM [88]. We note that the correlation coefficient between physics identity and perceived recognition is 0.84. This is consistent with Godwin et al.'s [39] and Kalender et al.'s [47] prior finding that students' physics perceived recognition (external identity) is the largest predictor of their physics identity (internal identity).

To analyze the predictive relationships among the constructs, we performed the path analysis. Apart from CFA, the path analysis in SEM gives regression coefficients β for paths between each pair of constructs and the value of each β is a measure of the strength of that relationship. Compared with a multiple regression model, the advantage of SEM is that we can estimate all of the regression links for multiple outcomes and factor loadings for items simultaneously, which improves the statistical power. The level of SEM model fit can also be represented by CFI, TLI, RMSEA and SRMR. We first analyzed the saturated SEM model that includes all possible links between different constructs, and then we used the modification indices to improve the model fit. We kept path links which were statistically significant in SEM path analysis. Before performing gender mediation analysis, we first tested the gender moderation relations between each pair of constructs using multi-group SEM (to investigate any interaction effects with gender), which includes testing of factor loadings, indicator intercepts, residual variances and regression coefficients. Results showed that in all of our models, strong measurement invariance holds and there is no difference in any regression coefficients by gender, which allowed us to perform the gender mediation analysis using SEM (see Appendix A for detailed multi-group SEM analysis results). We fit the two SEM models (Model 1 and Model 2) shown in Fig. 2 with our data and then compared the path analysis results (predictive relationships among the constructs) for these two models.

4. Results

4.1 Descriptive Statistics of Students' Motivational Beliefs at the Beginning and End of the Course

Here, we present the descriptive statistics of the students' pre- and post-motivational beliefs. As

Table 2. Pearson correlation coefficients of the constructs in the mediation model

Constructs	1	2	3	4	5
1. Engineering identity	–	–	–	–	–
2. Physics identity	0.34	–	–	–	–
3. Physics self-efficacy	0.37	0.70	–	–	–
4. Physics Interest	0.32	0.71	0.64	–	–
5. Physics perceived recognition	0.30	0.84	0.70	0.67	–

$p < 0.001$.

shown in Table 3, female students had significantly lower scores in all of the five motivational constructs. In particular, we note that the gender difference in students' physics identity is larger than that in engineering identity and students' physics identity is lower than engineering identity, which is expected because they are all engineering students. In addition, Table 3 shows that both male and female students' physics self-efficacy and physics identity deteriorated from pre to post. Moreover, female students' average scores on physics self-efficacy and physics interest decreased more than male students' did so that the gender differences in these two constructs became larger by the end of the course. Although students' average score on engineering identity also decreased from pre to post, this change is only statistically significant for male students.

We also conducted a one-way repeated measures MANOVA to analyze the changes in multiple dependent variables over time (from pre to post). The results show that female students' overall physics and engineering motivational beliefs decreased from pre to post (F(5,128) = 7.103 $p <$ 0.001, Wilks' Lambda = 0.78, partial eta squared (η_p^2 = 0.217). Partial eta squared values indicate effect sizes in one-way MANOVA with $\eta_p^2 \sim 0.01$ generally considered a small effect size, $\eta_p^2 \sim 0.06$ a medium effect size and $\eta_p^2 \sim 0.14$ a large effect size [89]. Follow-up univariate tests show that female students' physics identity (F(1,132) = 12.946, $p < 0.001$, $\eta_p^2 = 0.089$), self-efficacy (F(1,132) = 22.590, $p <$ 0.001, $\eta_p^2 = 0.146$), and interest (F(1,132) = 11.215, p = 0.001, $\eta_p^2 = 0.078$) statistically significantly decreased from pre to post. Similarly, male students' overall physics and engineering motivational beliefs also decreased from pre to post (F(5,189) = 4.361 $p =$ 0.001, Wilks' Lambda = 0.90, $\eta_p^2 = 0.103$). Follow-up univariate tests show that male students' physics identity (F(1,193) = 14.668, $p < 0.001$, $\eta_p^2 = 0.071$), self-efficacy (F(1,193) = 10.086, $p = 0.002$, $\eta_p^2 =$ 0.050), and engineering identity (F(1,193) = 6.739, $p = 0.01$, $\eta_p^2 = 0.034$) statistically significantly decreased from pre to post. Thus, the results of the one-way repeated measures MANOVA are consistent with the results shown in Table 3. In addition, we also report the percentages of students who selected each choice for each survey item in the pre and post-survey (see Appendix B), which are also consistent with the descriptive statistics shown in Table 3.

4.2 SEM Models Mediated by Motivational Factors

In this section, we will show the predictive relationships among students' motivational beliefs using SEM models. We first considered a model (Model 1) in which there are only covariances between each pair of constructs: physics perceived recognition, self-efficacy and interest. Thus, this model does not make assumptions about the predictive relationships between these three mediating constructs. We fit this model with our motivational survey data. The path analysis results are shown in Fig. 3 (a). The model fit indices suggest a good fit to the data: CFI = 0.976 (> 0.90), TLI = 0.969 (> 0.90),

Table 3. Descriptive statistics of female and male students' motivational beliefs at the beginning and end of the course

	Physics self-efficacy		**Statistics**		**Physics interest**		**Statistics**	
Gender	**pre**	**post**	***p* value**	**Cohen's *d***	**pre**	**post**	***p* value**	**Cohen's *d***
Male	3.09	3.00	0.046	0.20	3.05	3.00	0.394	0.08
Female	2.97	2.78	<0.001	0.42	2.86	2.72	0.033	0.26
p value	<0.001	<0.001			0.001	0.003		
Cohen's *d*	0.29	0.42			0.37	0.46		
	Physics perceived recognition		**Statistics**		**Physics identity**		**Statistics**	
Gender	**pre**	**post**	***p* value**	**Cohen's *d***	**pre**	**post**	***p* value**	**Cohen's *d***
Male	2.70	2.60	0.151	0.14	2.77	2.59	0.019	0.23
Female	2.44	2.36	0.310	0.12	2.42	2.23	0.043	0.24
p value	0.001	0.003			<0.001	<0.001		
Cohen's *d*	0.38	0.33			0.48	0.43		
	Engineering identity		**Statistics**					
Gender	**pre**	**post**	***p* value**	**Cohen's *d***				
Male	3.62	3.50	0.036	0.21				
Female	3.45	3.33	0.114	0.19				
p value	0.006	0.016						
Cohen's *d*	0.31	0.26						

The sample size is 346 (205 male students and 141 female students). Cohen suggested that a typical value $d \sim 0.2$ be considered a small effect size, $d \sim 0.5$ represents a medium effect size and $d \sim 0.8$ a large effect size.

RMSEA = 0.049 (< 0.08) and SRMR = 0.032 (< 0.08).

As shown in Fig. 3(a), there is a statistically significant regression line from gender to each of physics self-efficacy, perceived recognition, and interest, consistent with Table 3 showing that there are statistically significant gender differences in all of these three motivational constructs. However, the direct effects of gender on both physics identity and engineering identity are statistically insignificant (p = 0.21 for physics identity and p = 0.22 for engineering identity) even though female students' physics and engineering identities are statistically significantly lower than those of male students as shown in Table 3. This result indicates that the gender differences in students' physics and engineering identity are actually mediated by the other three physics motivational constructs. In addition, Fig. 3(a) shows that even though there is a strong covariance among physics self-efficacy, interest, and perceived recognition, students' physics perceived recognition is the strongest predictor of their physics identity (β = 0.58). This result is consistent with Hazari et al.'s [46] and Kalender et al.'s prior work [47].

Next, we consider a model (Model 2) in which physics perceived recognition predicts physics self-efficacy and interest, and physics self-efficacy predicts interest. The path analysis results are shown in Fig. 3 (b). This model also fits the data very well: CFI = 0.976 (> 0.90), TLI = 0.969 (> 0.90), RMSEA = 0.049 (< 0.08) and SRMR = 0.032 (< 0.08). We note that the direct effect of gender on physics perceived recognition in Model 2 is the same as that in Model 1. This is because in both models, gender is the only predictor of perceived recognition. On the other hand, the direct effects of gender on physics self-efficacy and interest are

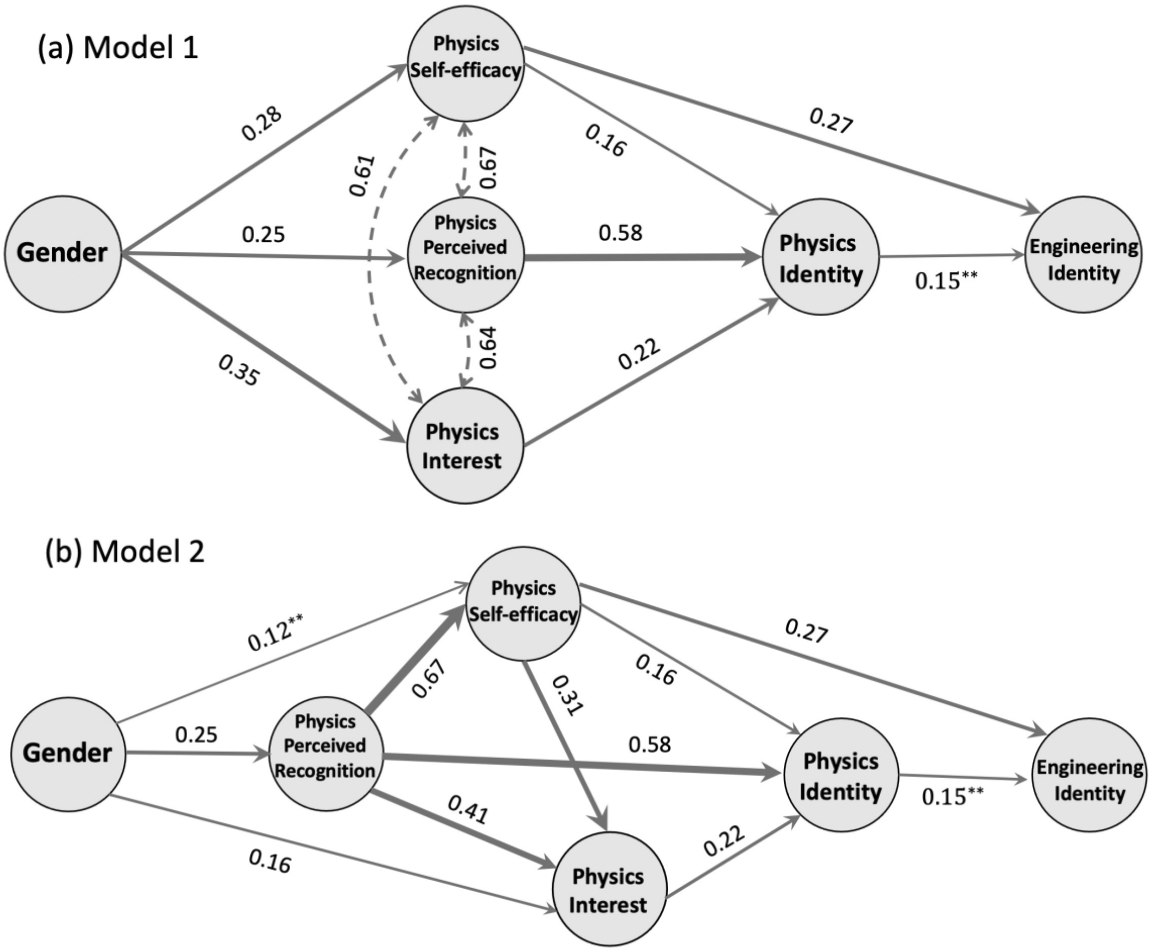

Fig. 3. Results of the path analysis part of the SEM models that show how the relationship between gender and engineering identity is mediated by physics self-efficacy, physics perceived recognition, physics interest and physics identity. (a) In Model 1, physics self-efficacy, perceived recognition and interest are correlated with each other. (b) In Model 2, physics perceived recognition predicts physics self-efficacy and interest, and physics self-efficacy predicts physics interest. The solid lines represent regression paths, and the numbers on the lines are standardized regression coefficients (β values), which represent the strength of the regression relations. Each regression line thickness qualitatively corresponds to the magnitude of β with $0.001 \leq p < 0.01$ indicated by **. All the other regression lines show relations with $p < 0.001$. For clarity, we have removed all statistically insignificant regression paths.

Table 4. Coefficient of determination (R^2) for various constructs in different models

Models	Constructs	R^2
Model 1 SE + Recog + Interest	Physics perceived recognition	0.06
	Physics self-efficacy	0.08
	Physics interest	0.12
	Physics identity	0.75
	Engineering identity	0.15
Model 2 Recog → SE → Interest	Physics perceived recognition	0.06
	Physics self-efficacy	0.49
	Physics interest	0.53
	Physics identity	0.75
	Engineering identity	0.15

All R^2 values are statistically significant with p values < 0.001. In Model 1, there are only covariances between each pair of constructs: physics self-efficacy (SE), perceived recognition (Recog), and interest. In Models 2, the arrows indicate the direction of the predictive relationships.

smaller in Model 2 compared with those in Model 1. This is because in Model 2, physics self-efficacy and interest are predicted by more constructs than in Model 1, and thus there is more correlated effect being controlled for when estimating the regression coefficients from gender to physics self-efficacy and interest.

To further understand the relationships among the motivational constructs in different models, we calculated the coefficients of determination R squared (fraction of variance explained) for each construct in each model (Table 4). We note that the R^2 of physics identity is 0.75 and the R^2 of engineering identity is 0.15 in both Model 1 and Model 2. This is because in both models, physics and engineering identity are predicted by the same constructs, even though the predictive relationships among the predictors are different in the two models. Similarly, since perceived recognition is only predicted by gender in both models, the R^2 of perceived recognition is the same across models. On the other hand, the R^2 of physics self-efficacy and interest are larger in Model 2 than in Model 1. This is because in Model 2, physics self-efficacy and interest are predicted by more constructs than they are in Model 1, and thus more variance in self-efficacy and interest is explained by Model 2.

5. Discussion

In this study, we investigated female and male undergraduate engineering students' engineering identity and physics motivational beliefs (including physics identity, self-efficacy, interest and perceived recognition) in a calculus-based introductory physics course. In particular, we focused on the predictive relationships among these engineering and physics motivational constructs, and how these constructs change from pre to post in the course.

Our results reveal that students' engineering identity is directly predicted by their physics identity and self-efficacy. Even though physics interest and perceived recognition do not have direct effects on engineering identity, they all indirectly predict engineering identity through physics identity. Since engineering is interdisciplinary in nature and physics is an important foundational discipline for engineering students, students' perception of their ability to do well in engineering may be influenced by their physics motivational beliefs, which can be influenced by their physics learning experiences. In addition, since physics is one of the disciplines that are believed to require intelligence for success [40, 41], doing well in physics may boost students' self-beliefs in learning other subjects such as engineering, while a low self-efficacy in physics may lead students to doubt their ability. According to our previous interviews with students, some students chose to major in engineering because of their earlier experience with mechanics in high school, while some other engineering students considered changing their majors because of their negative experience in a previous physics course.

Another important finding is that even though there are statistically significant gender differences disadvantaging women in all engineering and physics motivational constructs, gender does not directly predict engineering and physics identity. This means that the gender differences in students' engineering and physics identity are mediated through the other three physics motivational beliefs (physics self-efficacy, interest, and perceived recognition). According to a prior study, among an undergraduate engineering population, the gender difference in physics self-efficacy is the largest compared with the gender differences in students' self-efficacy in other STEM disciplines such as chemistry and math [43]. Thus, the gender difference in physics motivational beliefs may help explain the underrepresentation of women in "physics-heavy" engineering disciplines. Our study further indicates that we may be able to reduce the gender gap in students' engineering identity by eliminating the gender differences in physics motivational beliefs. For example, we can create a more inclusive and equitable learning environment for physics learning so that all students feel recognized as people who can do well in physics and other related disciplines.

However, our results show that the two direct predictors of students' engineering identity – physics identity and self-efficacy – actually decreased by the end of the physics course for both male and female students. Moreover, female students' physics self-efficacy dropped even more than male students' did, and the gender difference in physics self-efficacy became larger at the end of the course. These findings may partially explain the result that students' average score on engineering identity also decreased from pre to post, although this change is only statistically significant for male students. Overall, our results indicate that the current learning environment didn't help students develop a stronger engineering identity, and the gender difference in engineering identity is also maintained.

Physics courses are very important for engineering students because not only are they the foundation for engineering courses, but students' physics motivational beliefs can also influence their attitudes and beliefs toward engineering as well as their choice of careers. Due to societal stereotypes, physics is one of the disciplines that have a masculine image and are believed to require a natural ability to excel [42]. Studies have shown that these stereotypes and biases can negatively impact female students' motivational beliefs in physics [13, 90]. According to our study, these gender differences in physics motivational beliefs contribute to the gender difference in undergraduate engineering students' engineering identity. Thus, it is important to focus on the role played by physics courses in students' persistence and retention in engineering and engineering school should work with physics department to take effective measures to create an inclusive and equitable learning environment in which all students can develop a stronger identity in both physics and engineering. There are some research-based classroom interventions that have been shown to reduce gender gaps in students' performance in different types of classes (not necessarily focused on engineering students) [91-94]. However, to our knowledge, no intervention has investigated how engineering students' self-efficacy and identity are impacted by these interventions. Their impact on self-efficacy and identity of engineering students from different demographic groups should be studied in future studies. Appropriate interventions could particularly help underrepresented engineering students such as women in physics courses if they were designed well.

In this study, we used single item to measure students' physics identity and engineering identity. Even though these items are commonly used in studies involving physics and engineering identity [26, 32, 39, 60, 95–97], it would be helpful in future studies to develop more survey items for these identity constructs. Another limitation of the current study is that it only focuses on the underrepresentation of female students and not on other underrepresented demographic groups. In future studies, we intend to investigate motivational beliefs of students from other underrepresented groups such as ethnic/racial minority students. In addition, the data from this study was collected from one research university in the US. Similar studies in different types of institutions and in other countries would also be helpful for developing a deeper understanding of the relationships between students' physics motivational beliefs and their engineering identity.

6. Conclusion

Students' engineering identity is an important motivational belief that can influence students' retention in engineering as well as their short-term and long-term career goals. Introductory physics courses usually serve as a prerequisite for many engineering courses because they are foundation of many disciplines and contribute directly to engineering. In this study, we investigated how undergraduate engineering students' physics motivational beliefs predict their engineering identity in an introductory physics course. We find that students' engineering identity is directly predicted by their physics identity and self-efficacy and also indirectly predicted by their physics interest and perceived recognition (RQ3). However, our results show that both women and men's physics identity and self-efficacy decreased from the beginning to the end of the course (RQ1). In addition, there are statistically significant gender differences in all physics motivational beliefs and engineering identity, and the gender differences in physics self-efficacy and interest became larger at the end of the course (RQ2). Our results show that students' physics motivational beliefs play an important role in shaping their engineering identity; however, students' physics motivational beliefs decreased after the course, and current learning environment didn't help students develop a stronger engineering identity. Therefore, engineering school should reflect upon the role played by physics courses in undergraduate students' academic trajectory and retention in engineering and work with physics department to make intentional efforts to create an inclusive and equitable learning environment in which all students can develop a stronger identity in both physics and engineering.

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Appendix A: Multi-Group SEM Analysis

We conducted a multi-group analysis to examine whether the survey items were interpreted in a conceptually similar manner by female and male students, and whether the strength of relationships given by the standardized regression coefficients between any two constructs in the models differ for women and men.

We first tested for measurement invariance. In other words, we looked at whether the factor loadings, intercepts, and residual variances of the items are equal across gender in the model. Since Model 1 and Model

2 include the same motivational constructs, measurement invariance tests are the same for these two models. To test measurement invariance, we ran a set of increasingly constrained models and tested the differences between these models. First, we examined the configural invariance model, in which the number of constructs and the correspondence between constructs and items are the same across gender groups, but all parameters can vary freely in each group. The result indicated that configural invariance holds (CFI = 0.975 > 0.90, TLI = 0.967 > 0.90, RMSEA = 0.051 < 0.08, SRMR = 0.038 < 0.08). Second, to test for "weak" measurement invariance, we ran the model in which the item loadings were constrained to be equal across gender groups, but intercepts and residual variances were allowed to vary between groups. According to a likelihood ratio test, there was no statistically significant difference between the weak invariance model and the configural invariance model, so the weak measurement invariance holds (Chi-square difference $\Delta\chi^2 = 4.936$, degree of freedom difference $\Delta dof = 8$, $p = 0.764$). The third step is testing for "strong" measurement invariance. We ran the model in which both the item loadings and intercepts were constrained to be equal across gender groups, but the residual variances were allowed to differ. A likelihood ratio test shows that there was no statistically significant difference between the strong invariance model and the weak invariance model ($\Delta\chi^2 = 7.935$, $\Delta dof = 8$, $p = 0.440$) or the configural invariance model ($\Delta\chi^2 = 12.872$, $\Delta dof = 16$, $p = 0.682$), so strong measurement invariance holds. Finally, to test for "strict" measurement invariance, we ran the model in which the item loadings, intercepts, and residual variances were constrained to be equal across gender groups. This model was statistically significantly different from the strong invariance model ($\Delta\chi^2 = 18.378$, $\Delta dof = 9$, $p = 0.031$), therefore "strict invariance" did not hold. However, strict invariance is unlikely to hold in most situations. Therefore, since strong measurement invariance holds for this model, we proceeded on to test for structural invariance.

We tested for structural invariance to examine whether the regression coefficients among the motivational constructs are equal across gender. Since the regression relationships among the constructs are different in Model 1 and Model 2, we conducted the structural invariance test for Model 1 and Model 2 separately. We first ran a multi-group SEM for Model 1, in which all regression coefficients were constrained to be equal across gender groups in addition to the item loadings and intercepts. The model fit parameters for this model indicate a good fit (CFI = 0.975, TLI = 0.972, RMSEA = 0.047, SRMR = 0.050). According to the results of likelihood ratio tests, this model was not statistically significantly different from either the configural invariance model ($\Delta\chi^2 = 26.599$, $\Delta dof = 24$, $p = 0.324$) or the strong invariance model ($\Delta\chi^2 = 13.728$, $\Delta dof = 8$, $p = 0.089$). Thus, the regression pathways among the constructs do not have statistically significant differences across gender for Model 1. Then, we ran a multi-group SEM for Model 2, in which all regression coefficients were constrained to be equal across gender groups in addition to the item loadings and intercepts. This model also fits the data very well (CFI = 0.975, TLI = 0.972, RMSEA = 0.047, SRMR = 0.048). Similarly, there was no statistically significant difference between this model and the configural invariance model ($\Delta\chi^2 = 25.754$, $\Delta dof = 24$, $p = 0.366$) or the strong invariance model ($\Delta\chi^2 = 12.882$, $\Delta dof = 8$, $p = 0.116$). Thus, structural invariance also holds for Model 2.

Appendix B: Percentages of Students Who Selected Each Choice for Each Survey Item

In the main text, we investigated how students' motivational beliefs change from the beginning to the end of the course by comparing their average scores on the motivational constructs in the pre- and post-survey. Here, we present the percentages of female (Table 5) and male students (Table 6) who selected each answer choice from a 4-point Likert scale for each survey item. Students were given a score from 1 to 4 respectively with higher scores indicating greater levels of interest, self-efficacy, perceived recognition, physics identity, and engineering identity.

As shown in Table 5 and Table 6, for both female and male students, the percentages of students who selected 3 or 4 for most survey items under self-efficacy and physics identity decreased from pre to post, while the percentages of students who selected 1 or 2 increased. These results are consistent with the descriptive statics shown in Table 3, which show that both male and female students' self-efficacy and physics identity statistically significantly decreased from the beginning to the end of the course. In addition, by comparing Table 5 and Table 6, we found that for most survey items, the percentages of female students who selected 1 or 2 were larger than those of male students, while the percentages of female students who selected 4 were smaller than those of female students. These findings are also consistent with Table 3 showing that there were statistically significant gender differences in all motivational constructs studied.

Table 5. Percentages of female students who selected each choice from a 4-point Likert scale for each survey item in the pre- and post-survey

	Pre				Post			
Survey items	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**
SE1	4%	26%	65%	5%	9%	25%	60%	6%
SE2	2%	11%	78%	9%	4%	16%	74%	6%
SE3	0%	5%	72%	23%	6%	20%	61%	14%
SE4	0%	11%	72%	18%	5%	19%	65%	11%
Int1	6%	38%	44%	12%	8%	22%	46%	24%
Int2	1%	9%	70%	19%	4%	22%	63%	11%
Int3	0%	25%	62%	13%	5%	48%	39%	9%
Int4	1%	27%	54%	18%	6%	29%	54%	11%
Recog1	11%	39%	42%	7%	13%	38%	41%	8%
Recog2	12%	36%	45%	6%	12%	39%	40%	9%
Recog3	7%	50%	42%	1%	15%	54%	29%	2%
Physics identity	9%	48%	38%	6%	16%	49%	30%	5%
Engineering identity	0%	4%	46%	49%	1%	5%	52%	41%

The self-efficacy (SE) and interest (Int) items have the response scale: 1 = NO!, 2 = no, 3 = yes, and 4 = YES!, while the perceived recognition (Recog), physics identity, and engineering identity items have the response scale: 1 = strongly disagree, 2 = disagree, 3 = agree, and 4 = strongly agree.

Table 6. Percentages of male students who selected each choice from a 4-point Likert scale for each survey item in the pre- and post-survey

	Pre					Post		
Survey items	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**
SE1	2%	27%	60%	10%	3%	20%	64%	13%
SE2	0%	8%	72%	20%	0%	11%	68%	20%
SE3	0%	4%	60%	36%	3%	14%	55%	27%
SE4	0%	8%	69%	23%	0%	18%	65%	17%
Int1	4%	24%	42%	29%	4%	14%	38%	43%
Int2	2%	6%	66%	25%	3%	12%	60%	25%
Int3	2%	15%	61%	21%	3%	28%	47%	21%
Int4	1%	15%	62%	22%	4%	25%	49%	21%
Recog1	4%	31%	49%	16%	9%	26%	49%	15%
Recog2	6%	33%	43%	18%	10%	33%	42%	15%
Recog3	5%	35%	54%	5%	13%	35%	46%	6%
Physics identity	3%	30%	52%	14%	11%	32%	45%	12%
Engineering identity	1%	1%	32%	66%	1%	4%	39%	56%

The self-efficacy (SE) and interest (Int) items have the response scale: 1= NO!, 2 = no, 3 = yes, and 4 = YES!, while the perceived recognition (Recog), physics identity, and engineering identity items have the response scale: 1 = strongly disagree, 2 = disagree, 3 = agree, and 4 = strongly agree.

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