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Exploring Suppression-Like Effects in Logistic Modeling of Stem Participation: Engagement and Self-Efficacy as Correlated Predictors

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ABSTRACT

This study examines the joint statistical roles of STEM engagement and STEM self-efficacy in modeling collegiate students' participation in STEM disciplines. Survey data from students at Texas A&M International University were analyzed using exploratory factor analysis, reliability assessment, group comparisons, and a sequence of nested binary logistic regression models. Two reliable latent constructs, STEM engagement and STEM self-efficacy, were identified. In separate logistic models, both engagement and self-efficacy positively predicted STEM participation. However, the engagement coefficient changed from positive ($B = 0.506$, $p = 0.009$) in the engagement-only model to negative ($B = -0.568$, $p = 0.047$) after adjustment for self-efficacy, while self-efficacy remained strongly positive ($B = 1.593$, $p < 0.001$). The predictors were substantially correlated ($r = 0.698$), although variance inflation factors were only 1.95. Likelihood-ratio testing indicated that engagement provided statistically significant incremental information beyond self-efficacy ($\chi^2 = 4.13$, $p = 0.042$), whereas an engagement-by-self-efficacy interaction was not supported. Model comparison therefore suggests a suppression-like coefficient sign reversal rather than a simple interaction effect. These findings illustrate the importance of examining correlated latent predictors jointly and caution against interpreting marginal and adjusted associations as equivalent.2020 Mathematics Subject Classifications: 62H25, 62J12, 62P25.

Keywords and Phrases: exploratory factor analysis, logistic regression, suppression effect, coefficient sign reversal, correlated predictors, STEM participation.

INTRODUCTION

Science, Technology, Engineering, and Mathematics (STEM) fields represent a substantial and expanding portion of the U.S. labor market. In 2023, approximately 20.7 million workers were employed in STEM occupations, which generally offer median wages above the national median [5]. STEM occupations are also projected to grow faster than non-STEM occupations [17]. These trends motivate continued investigation of the factors associated with students' entry into and persistence within STEM pathways.

Self-efficacy has repeatedly been identified as an important psychological factor in students' decisions to enter and remain in STEM fields [7, 18]. Engagement is likewise associated with educational experiences, support, and participation, but engagement and self-efficacy are conceptually related constructs. When correlated predictors are entered jointly into a regression model, the adjusted coefficient of one predictor may differ substantially from its marginal association with the outcome. In some cases, a coefficient can even reverse sign after adjustment.

Such coefficient reversals are statistically important because they complicate substantive interpretation. A positive bivariate association does not necessarily imply a positive partial regression coefficient when another correlated predictor is controlled. Suppression-like patterns may arise when shared predictor variance and outcome-relevant unique variance operate differently within a multivariable model. Accordingly, examining only a single fitted logistic regression may obscure how predictor coefficients evolve across nested model specifications.

The present study examines STEM engagement and STEM self-efficacy as correlated latent constructs associated with current STEM participation. Exploratory factor analysis is first used to identify the construct structure of the survey items. A sequence of logistic regression models is then estimated: an engagement-only model, a self-efficacy-only model, a combined additive model, and an interaction model. Model coefficients, information criteria, McFadden's pseudo-R^2, area under the receiver operating characteristic curve (AUC), variance inflation factors, and likelihood-ratio tests are used to evaluate the statistical role of each predictor.

The primary objectives are to determine whether (i) engagement and self-efficacy form reliable latent constructs, (ii) each construct is associated with STEM participation when modeled separately, (iii) the engagement coefficient changes after adjustment for self-efficacy, and (iv) the observed pattern is better explained by an additive suppression-like structure or by an engagement-by-self-efficacy interaction.

Data Collection and Survey Design

Participants and Data Collection

A Qualtrics survey was administered by email to registered students at Texas A&M International University. The final dataset consisted of 224 student responses. After excluding incomplete observations, 223 responses were retained for inferential modeling and regression analysis. Of these respondents, 77 students, approximately 35%, reported currently pursuing a STEM field, whereas 146 students, approximately 65%, reported pursuing non-STEM fields. Among the analytic sample, 115 respondents identified as female and 107 as male, with one missing gender response. Academic classification included 40 freshmen, 98 sophomores, 42 juniors, 31 seniors, and 12 graduate students. The mean age was 20.93 years (SD = 4.67; range = 17–53) among respondents with valid age data. Because the total number of students who received the survey invitation was not available, a response rate could not be calculated.

Participation was voluntary, and responses were anonymized prior to analysis. The study protocol was reviewed and approved by the Institutional Review Board at Texas A&M International University under protocol number IRB-2025-30.

Survey Instrument

The survey was developed for the present study to examine students' secondary-school experiences, STEM-related attitudes and perceptions, and subsequent STEM participation. The survey included nine five-point Likert-scale items designed to measure students' perceptions of STEM engagement and STEM self-efficacy. Responses ranged from 1, Strongly Disagree, to 5, Strongly Agree. The instrument included items related to teacher encouragement, STEM interest, academic support, peer encouragement, confidence in STEM ability, STEM belonging, and perceived STEM career accessibility.

The binary outcome variable identified whether respondents were currently pursuing a STEM major or career path. This variable served as the dependent variable in the logistic regression analyses.

Data Preparation

The survey data were exported from Qualtrics in CSV format and processed using Python statistical libraries. The first two metadata rows in the Qualtrics export were removed. Likert-scale responses were recoded as

1 = Strongly Disagree,   2 = Disagree,   3 = Neutral,   4 = Agree,   5 = Strongly Agree.

Incomplete responses and invalid entries were treated as missing values. Composite variables were constructed by averaging items associated with each validated construct. Based on the exploratory factor loading structure, engagement was computed using Q14 1, Q14 3, Q14 4, Q14 5, and Q14 6, whereas self-efficacy was computed using Q14 2, Q14 7, and Q14 9. Current STEM participation was defined directly from respondents' yes/no

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response to the survey question, "Are you currently pursuing a STEM major or career path?" Responses were coded as 1 for Yes and 0 for No.

$$STEM = \begin{cases} 1, & \text{if currently pursuing a STEM major or career path,} \\ 0, & \text{otherwise.} \end{cases}$$

The final inferential dataset contained 223 complete observations.

Construct Validation and Descriptive Analysis

Statistical Preparation for Factor Analysis

Exploratory Factor Analysis (EFA) was used to identify latent dimensions underlying the correlated survey items. Sampling adequacy was evaluated using the Kaiser–Meyer–Olkin (KMO) measure, and Bartlett's test of sphericity was used to assess whether the correlation matrix differed significantly from an identity matrix. Given the five-point response format, the Likert items were treated as approximately continuous for the exploratory analysis, and the EFA was based on Pearson correlations.

Parallel analysis and scree plot inspection were examined to inform factor retention. Although parallel analysis suggested a one-factor solution, a two-factor solution was retained to examine the distinct dimensions of engagement and self-efficacy represented by the survey items. Oblimin rotation was used to allow the factors to be correlated.

Factorability Diagnostics

The overall KMO statistic was 0.886, indicating strong sampling adequacy for factor analysis. Bartlett's test of sphericity was highly significant ($\chi^2 = 829.58$, $p < 0.001$), rejecting the null hypothesis that the correlation matrix was an identity matrix. These diagnostics supported the use of EFA.

Exploratory Factor Analysis

A two-factor solution was estimated using minimum residual (MINRES) extraction with oblimin rotation. The estimated factor correlation was 0.785, and the two factors accounted for approximately 45.0% of the variance. The EFA suggested two correlated latent dimensions corresponding to STEM engagement and STEM self-efficacy. Table 1 presents the factor loadings.

Table 1: Exploratory Factor Analysis Loadings

Item	Factor 1	Factor 2	Interpretation
Q14 1	0.774	−0.118	Engagement
Q14 2	0.072	0.746	Self-efficacy
Q14 3	0.540	0.188	Engagement
Q14 4	0.654	−0.017	Engagement
Q14 5	0.724	0.046	Engagement
Q14 6	0.585	0.242	Engagement
Q14 7	−0.027	0.895	Self-efficacy
Q14 8	0.241	−0.055	Weak loading
Q14 9	0.077	0.573	Self-efficacy

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Item Q14 8 exhibited weak loadings on both factors and was excluded from composite scale construction. The remaining items formed two interpretable exploratory composite measures. Because these measures were derived exploratorily, the labels ‘engagement’ and ‘self-efficacy’ are used as descriptive summaries of the observed item groupings rather than as independently confirmed measurement constructs.

Reliability Assessment

Internal consistency was assessed using Cronbach’s alpha. The engagement scale demonstrated good reliability ($\alpha = 0.833$), and the self-efficacy scale also demonstrated good reliability ($\alpha = 0.809$).

Table 2: Cronbach’s Alpha Reliability Coefficients

Scale	Cronbach’s Alpha	Interpretation
Engagement	0.833	Good reliability
Self-efficacy	0.809	Good reliability

Descriptive Statistics

Table 3 summarizes the validated composite constructs.

Table 3: Descriptive Statistics for Validated Constructs

Variable	Mean	SD	Min	Max
Engagement	3.20	0.78	1.00	5.00
Self-efficacy	3.39	0.85	1.00	5.00

The Pearson correlation between engagement and self-efficacy was $r = 0.698$, indicating a substantial positive association between the two predictors.

Inferential Modeling of STEM Participation

Group Comparisons Between STEM and Non-STEM Students

Independent-samples t-tests were conducted to compare the validated constructs between students pursuing and not pursuing STEM pathways. STEM students reported significantly higher engagement, $t(221) = 2.70$, $p = 0.007$, and significantly higher self-efficacy, $t(221) = 6.41$, $p < 0.001$.

Table 4: Group Comparisons Between STEM and Non-STEM Students

Variable	t-Statistic	p-value
Engagement	2.70	0.007
Self-efficacy	6.41	< 0.001

These marginal comparisons indicate positive associations of both engagement and self-efficacy with STEM participation. However, they do not determine the partial association of either construct after adjustment for the other.

Logistic Regression Framework

Let Y_i denote STEM participation for student i, where $Y_i = 1$ for STEM participation and $Y_i = 0$ otherwise. Four logistic regression models were considered.

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The engagement-only model was

$$log(\frac{P(Y_i = 1)}{1 - P(Y_i = 1)}) = \beta_0 + \beta_1 E_i$$

where E_i denotes engagement.

The self-efficacy-only model was

$$log(\frac{P(Y_i = 1)}{1 - P(Y_i = 1)}) = \beta_0 + \beta_1 S_i$$

where S_i denotes self-efficacy.

The combined additive model was

$$log(\frac{P(Y_i = 1)}{1 - P(Y_i = 1)}) = \beta_0 + \beta_1 E_i + \beta_2 S_i$$

Finally, the interaction model was

$$log(\frac{P(Y_i = 1)}{1 - P(Y_i = 1)}) = \beta_0 + \beta_1 E_i + \beta_2 S_i + \beta_3 E_i S_i$$

For the interaction model, engagement and self-efficacy were mean-centered before constructing the product term.

Model parameters were estimated by maximum likelihood. Odds ratios were obtained by exponentiating the estimated coefficients. Model fit was evaluated using Akaike's information criterion (AIC), Bayesian information criterion (BIC), McFadden's pseudo-R^2, and AUC. Nested models were compared using likelihood-ratio tests.

Single-Predictor and Combined Logistic Models

Table 5. Coefficient Comparison Across Logistic Regression Models

Model	Predictor	B	SE	p	OR	95% CI for OR
Engagement only	Engagement	0.506	0.193	.009	1.66	[1.14, 2.42]
Self-efficacy only	Self-efficacy	1.228	0.224	<.001	3.42	[2.20, 5.30]
Combined	Engagement	−0.568	0.286	.047	0.57	[0.32, 0.99]
Combined	Self-efficacy	1.593	0.299	<.001	4.92	[2.74, 8.84]
Interaction	Engagement	−0.615	0.293	.036	0.54	[0.30, 0.96]
Interaction	Self-efficacy	1.608	0.298	<.001	4.99	[2.78, 8.96]
Interaction	Engagement × Self-efficacy	0.137	0.216	.524	1.15	[0.75, 1.75]

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Note. For the interaction model, engagement and self-efficacy were mean-centered before constructing the interaction term.

In the engagement-only model, engagement was a significant positive predictor of STEM participation (B = 0.506, $p = 0.009$), corresponding to an odds ratio of approximately 1.66. Thus, before adjustment for self-efficacy, a one-unit increase in engagement was associated with approximately 66% higher odds of STEM participation.

In the self-efficacy-only model, self-efficacy was a strong positive predictor (B = 1.228, $p < 0.001$), with an odds ratio of approximately 3.42.

A different pattern emerged in the combined model. Self-efficacy remained strongly positive (B = 1.593, $p < 0.001$; odds ratio = 4.92), whereas the engagement coefficient changed sign from +0.506 to −0.568 and was marginally significant at the 0.05 level ($p = 0.047$; odds ratio = 0.57).

The observed change 0.506 → −0.568 is a coefficient sign reversal after adjustment for a correlated predictor.

The variance inflation factor was 1.95 for both engagement and self-efficacy. These values do not indicate severe conventional multicollinearity. Thus, the sign reversal should not be attributed automatically to extreme variance inflation.

In 5,000 bootstrap resamples, the engagement coefficient changed from positive in the engagement-only model to negative in the combined model in 96.5% of samples, indicating that the sign-reversal pattern was stable across most bootstrap resamples.

Model Comparison

Table 6 summarizes model performance.

Table 6: Comparison of Logistic Regression Models

Model	AIC	BIC	McFadden R^2	AUC
Engagement only	284.13	290.94	0.025	0.638
Self-efficacy only	252.06	258.87	0.137	0.752
Combined	249.92	260.14	0.151	0.753
Interaction	251.53	265.16	0.153	0.756

The combined model produced the lowest AIC and the largest pseudo-R^2 among the additive models. The self-efficacy-only model produced the lowest BIC, reflecting the stronger penalty BIC applies to additional model complexity. AUC increased only slightly from 0.752 in the self-efficacy-only model to 0.753 in the combined model.

Likelihood-ratio tests provided further evidence regarding incremental predictor contribution. Adding self-efficacy to the engagement-only model substantially improved fit ($\chi^2 = 36.21$, $p < 0.001$). Adding engagement to the self-efficacy-only model also improved fit, although more modestly ($\chi^2 = 4.13$, $p = 0.042$). Therefore, engagement retained statistically detectable conditional information beyond self-efficacy despite the reversal of its adjusted coefficient.

In repeated stratified 10-fold cross-validation, mean AUC values were 0.637, 0.754, and 0.750 for the engagement-only, self-efficacy-only, and combined models, respectively, indicating little incremental predictive discrimination from adding engagement to self-efficacy. Additional diagnostics indicated no clear violation of

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linearity in the logit or evidence of poor calibration, and no single observation appeared to exert undue influence on the combined model.

Interaction Model

The engagement-by-self-efficacy interaction coefficient was not statistically significant ($B = 0.137$, $p = 0.524$). A likelihood-ratio comparison of the interaction model with the combined additive model was also nonsignificant ($\chi^2 = 0.39$, $p = 0.532$).

These results provide no evidence that the association between engagement and STEM participation changes multiplicatively across levels of self-efficacy. The statistical pattern is therefore more consistent with an additive suppression-like coefficient reversal than with a conventional interaction effect.

DISCUSSION

The principal statistical finding of this study is the reversal of the engagement coefficient across logistic regression specifications. Engagement was positively associated with STEM participation in the group comparison and in the engagement-only logistic model. However, after self-efficacy was entered into the model, the engagement coefficient became negative. In contrast, self-efficacy remained strongly and consistently positive.

This distinction between marginal and adjusted associations is central to the interpretation of correlated predictors. The positive coefficient for engagement in the single-predictor model reflects its overall association with STEM participation, including variance shared with self-efficacy. Because engagement and self-efficacy were substantially correlated ($r = 0.698$), the combined model separates their partial associations. Once the strong self-efficacy component is held constant, the residual contribution associated with engagement is estimated differently, producing the observed sign reversal.

The pattern is appropriately described as suppression-like rather than as definitive proof of a classical suppression mechanism. Because logistic-regression coefficients are non-collapsible, changes in coefficient magnitude across nested models may also arise from properties of the logistic model and should not be attributed solely to a substantive suppression mechanism. The engagement coefficient is near the conventional significance threshold in the combined model, and the modest difference in AUC between the self-efficacy-only and combined models indicates limited additional predictive discrimination. Nevertheless, the likelihood-ratio test shows that adding engagement to self-efficacy significantly improves model fit. Engagement therefore appears to contain conditional explanatory information that is not captured entirely by self-efficacy.

The variance inflation factor (VIF) results are also informative. Both predictors had VIF values of 1.95, which are well below common thresholds used to flag severe multicollinearity. Consequently, the coefficient reversal should not be dismissed merely as an artifact of extreme collinearity. Rather, it illustrates how shared predictor variance can alter coefficient interpretation even when conventional collinearity diagnostics appear acceptable.

The nonsignificant interaction further clarifies the model structure. There was no evidence that the effect of engagement varied multiplicatively with self-efficacy. Instead, the statistical issue concerns the redistribution of shared and unique predictor information within the additive logistic model. This distinction is important because interaction and suppression are conceptually different phenomena and require different interpretations.

From a STEM education perspective, self-efficacy emerged as the most robust predictor of current STEM participation. This finding is consistent with prior research emphasizing self-efficacy as a central mechanism in STEM interest, persistence, and career decision-making [7, 10, 16, 18]. Engagement should not, however, be interpreted as inherently detrimental. The marginal association of engagement with STEM participation was positive. The negative adjusted coefficient is conditional on holding self-efficacy constant and should not be interpreted as a simple causal effect of increasing engagement. Because the models did not adjust for demographic, academic, or socioeconomic covariates, the observed coefficient reversal could also partly reflect omitted-variable effects.

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The results also demonstrate the value of sequential model specification. Had only the combined model been reported, the negative engagement coefficient might have appeared counterintuitive or been interpreted as a substantive negative effect. Had only the single-predictor model been reported, the coefficient reversal would have remained hidden. Comparing nested models reveals a more nuanced statistical relationship among engagement, self-efficacy, and STEM participation.

CONCLUSION

This study combined exploratory factor analysis and sequential logistic regression modeling to examine STEM engagement and self-efficacy as correlated predictors of STEM participation. The factor analysis identified two reliable latent constructs, and both constructs were positively associated with STEM participation when considered marginally.

The central result was a sign reversal in the engagement coefficient. Engagement positively predicted STEM participation when modeled alone but became negative after adjustment for self-efficacy. Self-efficacy remained a strong positive predictor across specifications. Model comparison showed that engagement contributed statistically significant incremental information beyond self-efficacy, although the improvement in predictive discrimination was modest. No engagement-by-self-efficacy interaction was supported.

These findings provide an applied illustration of how coefficient interpretation can change when correlated latent predictors are entered jointly into a logistic regression model. The results support a cautious suppression-like interpretation and emphasize that marginal and partial associations should not be treated as interchangeable. More broadly, the study highlights the importance of nested model comparison, collinearity diagnostics, and careful coefficient interpretation in applied statistical research involving correlated psychosocial constructs.

Appendix A. Survey Instrument

Table 7 presents the Likert-scale survey items used to measure STEM engagement and STEM self-efficacy.

Table 7: STEM Engagement and Self-Efficacy Survey Items

Statement	1	2	3	4	5
My high school teachers encouraged me to pursue STEM.					
I felt confident in my ability to succeed in STEM subjects.					
STEM subjects were presented as creative and interesting.					
I received enough academic support in math and science.					
I felt encouraged by my peers to pursue STEM.					
Working with my STEM classmates made me confident in my STEM skills.					
I felt like I was a good fit for STEM courses.					
Talent was necessary to be in STEM, not just effort.					
I see STEM careers as accessible and rewarding.					

Appendix B. Bootstrap Stability Analysis

Bootstrap resampling was used to assess the stability of the engagement coefficient sign reversal across model specifications.

Table B1. Bootstrap Stability Summary

Bootstrap measure	Result
Number of bootstrap resamples	5,000
Engagement positive in engagement-only model	99.5%
Engagement negative in combined model	97.0%
Positive-to-negative sign reversal	96.5%
Median adjusted engagement coefficient	-0.570

Note. The percentile 95% bootstrap interval for the adjusted engagement coefficient was [-1.221, 0.025].

Appendix C. Repeated Stratified Cross-Validation

Predictive discrimination was evaluated using repeated stratified 10-fold cross-validation with 10 repeats.

Table C1. Cross-Validated AUC by Logistic Regression Model

Model	Mean cross-validated AUC
Engagement only	0.637
Self-efficacy only	0.754
Combined	0.750

Note. Stratification preserved the STEM/non-STEM outcome distribution within folds.

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