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Programming Self-Efficacy is Moderated by an Ecological Belonging Intervention, Race/Ethnicity, and Gender*

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STEM environments are often "unwelcoming" and impact students' sense of belonging, particularly in fields with long-standing underrepresentation of women, Black, Latiné, and Indigenous students. Belonging interventions have shown promise in addressing these issues to improve outcomes. A new variation is an ecological belonging intervention that has been contextualized to a specific course within a predominantly White institution (PWI) suggests that struggle in the course is a normal and surmountable experience, and that struggle does not signal a lack of belonging. In-class, students participated in peer-to-peer and faculty-led discussions of overcoming struggle through self-reflection and shared experiences with past struggle. This quasi-experimental study of 1110 students enrolled in a 1st year engineering programming course examines impacts on programming self-efficacy. The study used a quasi-experimental design with some treatment and control sections of the programming course. With PROCESS in SPSS, the moderation of programming self-efficacy by intervention condition from pre-test to post-test was tested. In addition, the moderation of intervention effect by race/ethnicity (Black, Latiné, white, and Asian), and gender (women and men) was tested. The moderated moderation analyses showed significant interactions for Black (condition by Black $\beta = -2.00$, p = 0.009; PSE by condition by Black $\beta = 0.81$, p = 0.003), White (condition by White $\beta = 0.59$, p = 0.04), and gender (PSE by condition by gender $\beta = 0.27$, p = 0.005) models such that the intervention supported student post-programming self-efficacy. The ecological belonging intervention supports students in developing programming self-efficacy as part of an introductory programming course.

Keywords: intervention; programming; self-efficacy; race/ethnicity; gender

1. Introduction

The increasing need for qualified engineers to meet the challenges of a technologically advanced society and economy has been recognized for some time. Much effort and research has been put into improving engineering education; however, the graduation rate for engineers requires a significant increase to continue meeting demand. Within engineering, programming skills represent an essential skill set for engineering bachelor's degrees and careers [1, 2]. Universities continue to increase programming offerings beyond computer science majors [2].

1.1 Problem

However, many students continue to see programming as difficult to learn and hold low estimations of their programming abilities with significant disparities between groups of students with Asian, Black, Native American, Hispanic, non-binary, and woman identities [3–10].

One's belief about one's ability to complete specific tasks, called self-efficacy [11–13] shapes actions and can help direct effort in pursuit of broader goals [13, 14]. Self-efficacy has been strongly tied to academic achievements and specific skill development [15]. In STEM courses, self-efficacy is often a major predictor of success [16, 17]. Unfortunately, disparities in self-efficacy for women and Black and Latiné students are regularly observed in STEM [18–24]. Regarding programming self-efficacy, studies have observed that differences in pre-college access compound disparities in self-efficacy in computer-related studies for students with Asian, Black, Native American, Hispanic, non-binary, and woman identities [3–8]. Further, lower self-efficacy may contribute to higher attrition from engineering majors, particularly those with heavier programming requirements. When students do not feel they belong in an environment due to larger stereotypes, initial course struggles can be interpreted as signs of lower ability [25]. Brief psychosocial interventions often seek to counter such factors [26–30], but have not been explored extensively in programming contexts with only recent exceptions [30]. In this research, we explore the impact of a belonging intervention on general programming self-efficacy for Black, Latiné, and women students. In this exploration of belonging and programming self-efficacy, we seek to determine if belonging is a valuable route to improved self-efficacy for underrepresented groups in engineering and computing.

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1.2 Literature Survey

Programming self-efficacy reflects students' beliefs that they can complete coding-specific tasks successfully. Experience with programming and computing relates positively to self-efficacy. Past computing experience positively predicts programming and computing self-efficacy [6, 31–33]. However, pre-college access and exposure to programming remain uneven contributing to disparities in experience [3–5, 34, 35].

Gender-based disparities in retention, major choice, and academic performance in many STEM areas have been associated with differences in self-efficacy between women and men [36–41]. Although some progress in women's self-efficacy has been identified [42], women's self-efficacy has been observed to decrease on average throughout college in many STEM contexts [43] including in programming [44, 45]. Differences in self-efficacy between women and men tend to not correctly reflect actual differences in academic performance: women often express lower self-efficacy than merited based on their grade performance, including in programming and other STEM courses in which they receive higher grades than men [46, 47]. The intersection of oppression experienced by Black and Latiné women generates further differences in self-efficacy and learning outcomes [48].

Similarly, self-efficacy disparities exist for Black and Latiné students in classroom settings [49]. Even as Black and Latiné students express lower self-efficacy than their white peers, socioeconomically disadvantaged Black and Latiné students express lower self-efficacy than their wealthier same-race peers [50]. Asian students report lower self-efficacy on average, which is not associated with their academic performance [51]. Further, self-efficacy in computing was significantly lower for Asian and Black students in competitive admission departments [5]. Similarly, Ojha and associates (2024) found identifying as Asian, Black, Native, or Latiné were significantly associated with lower computing self-efficacy.

1.2.1 Self-Efficacy and Belonging

In engineering, women often identify self-efficacy and a lack of belonging as key factors that lead to their lower retention [42, 43, 46, 47, 51, 52]. A significant decrease in feelings of inclusion in the first year of engineering coursework contributed to uneven positive progress in self-efficacy [42]. Larger issues have been identified in the engineering majors with especially high levels of programming like electrical and mechanical engineering [1] which are also especially dominated by White and Asian men [53]. Lower self-efficacy beliefs of women can result from lower feelings of belonging [42] due to broader cultural stereotypes as well as macro and microaggressions within courses [54–56]. In essence, when students receive messages that they do not belong, initial struggle in unfamiliar topics like programming leads the students to interpret the struggle as due to an inherent lack of ability [44, 45]. where students often struggle in introductory programming coursework.

Therefore, one opportunity to address disparities in programming self-efficacy may be to address feelings of belonging and inclusion within engineering courses, particularly those with programming foci. Specifically, addressing disparities in belonging of Black, Latiné, and women students could provide a valuable avenue to increasing self-efficacy. As such, we sought to investigate the effect of a belonging intervention on programming self-efficacy in a first-year engineering programming course required for all undergraduate engineering students.

1.2.2 Belonging Intervention

Short psychosocial interventions at the beginning of a course that focus on students' sense of belonging can produce positive effects years following the intervention [57]. For example, following an online 45-minute social belonging intervention, Black students' performance improved [58] with longer-term positive effects demonstrated post-graduation [27]. In an online intervention, students read stories of past students overcoming adversity as a demonstration of overcoming struggle. However, when studied at scale, similar belonging intervention results produced mixed efficacy [59, 60], potentially because the intervention was not sufficiently customized and integrated into each classroom's context.

1.2.3 The Brief Ecological Belonging Intervention

In this work, an ecological belonging intervention was created that involved extensive contextualizing of the intervention details to the specific course that received the intervention [61]. Based on prior social belonging interventions to convey that typical struggle is normal and surmountable [26], this ecological intervention focuses on the environment through peer-to-peer and faculty-student discussions of overcoming struggle with activities for groups of 3–5 peers and the entire class. It is important to note that this intervention focuses on typical college struggles to reshape interpretations that students may be the only ones experiencing common challenges and disrupt illicit messages that can negatively shape self-efficacy and belonging. Previous applications of the course-adapted ecological intervention in an introductory physics course reduced historically significant gender-based achievement gaps and improved overall attendance [28].

A similar implementation was developed for a required first-year, second-semester programming course with achievement gaps for Black and Latiné students [28, 30, 61]. After a short training course sequence, the course instructors delivered the intervention during one class session of about 45 minutes during the first week of classes. The intervention implementation early in the course established a classroom norm for struggle as temporary and normal and something that students are capable of overcoming. Briefly, the intervention involved five activities. First, the instructor described challenges students have typically encountered or may already be navigating as early-career college students such as college adjustments, time and workload management, in addition to the challenges of the course material. Second, students wrote about a current struggle they are experiencing, how they think it can be addressed, and how it will be overcome in the future. Third, the instructor shares stories from real students who have struggled and completed the course. The stories come from recent students in the course in narrative form to convey the process of encountering struggle and overcoming it successfully. Fourth, students share stories of struggles with three to five student peers to normalize struggle and to help identify opportunities to overcome struggle. Fifth, as part of a large group discussion led by the instructor, students were invited to share insights with the whole class. The discussion prompts students to identify struggles, how they are common, and to identify common experiences in the group and the class [62]. The recognition that struggle is normal assists students in integrating the concept that struggle does not single students out as not belonging in the class or in engineering. Openly sharing struggles with peers and instructor is intended to create a more supportive environment within the ecology of the classroom.

1.3 Hypothesis, Aims, and Objectives

Our research questions focus on whether the brief Ecological Belonging Intervention changed programming self-efficacy beliefs from pre-test to post-test relative to control groups that did not receive the intervention and if the change depended on race/ethnicity or gender. Our interest focuses beyond belonging to understand the effects of the treatment on longer-term constructs such as self-efficacy and in this analysis programming self-efficacy. The influence of this intervention specifically on belonging has been demonstrated elsewhere (see [30, 63–66]). In this set of analyses, we seek to answer the following research questions.

(1) Does the Brief Ecological Belonging Intervention moderate the relationship between pre- and post-assessment programming self-efficacy beyond past programming experience and course grade?
(2) Does race/ethnicity (Black, Latiné , Asian, or White) moderate the treatment effect of the intervention on post-assessment programming self-efficacy?
(3) Does gender moderate the treatment effectiveness of the intervention on post-assessment programming self-efficacy?

To answer the exploratory research questions moderated mediation analysis allows testing of the interaction of the variables in direct relationships. Multiple models are required to identify the distinct influences of race/ethnicity and gender on the moderation of the treatment effectiveness.

2. Method

Data for these analyses come from a larger project investigating a belonging intervention in an early engineering programming course focus on programming within MATLAB, the programming environment that is especially common in many engineering disciplines. The main programming topics covered in this course include an introduction to the MATLAB programming environment, indexing, descriptive statistics, relational and logical operators, selection structures, loops, plotting and displays, user-defined functions, and regression (linear and non-linear), and a team design project implementing these concepts to make an engineering decision.

Approximately 1530 engineering students from a large Midwestern predominantly White institution (PWI) university were enrolled in the targeted programming course in the Spring 2023 semester. Students in seven sections received the intervention and students in six other sections were 'business as usual.' The distribution of students in the intervention vs. control sections was not significantly different by race/ethnicity, gender, or international status. Analyses focused on 1110 students who completed both pre- and post-intervention surveys that were necessary for these analyses (i.e., programming self-efficacy and demographic identities).

The resulting sample reflects the PWI context of the intervention, with 64% of students identifying as White, 26% Asian, 8% Latiné, and 2% Black. Gender representation in the sample reflects typical enrollments in engineering in the U.S. with 63% men, 33% women, 1% responding non-binary/gender-queer, and 2% selected prefer to not respond.

2.1 Sampling Procedures

With a top-down and bottom-up strategy, faculty were recruited to participate in the intervention. A presentation about the intervention and previous success to department leadership generated administrative support. A similar presentation to course instructors and an email request led to instructor volunteers for the course "business-as-usual" (control) and intervention sections (refer to [67] for more details). Four instructors received training to conduct the intervention, and three instructors conducted the course without the intervention session as they would have normally.

In the week before classes started, students were invited to participate in a pre-intervention survey via the Qualtrics online platform. The response rate for the pr-intervention survey was 73%. A post-intervention survey was distributed during the week 13 out of 15 to capture responses near the end of the semester and to avoid high-stress final exams, project deadlines, and other course surveys. The response rate for the post-intervention survey was slightly higher at 79%. Participants who started the survey were awarded two extra credit points per survey to earn a maximum of four extra credit points for the course, and students who did not want to participate were offered other options for extra credit. Participants were not aware that the intervention activity was part of an experiment. Control sections and participants completed the same pre- and post-intervention surveys for the same extra credit opportunity. Some student information was collected from institutional records as described in the Measures section. The Institutional Review Boards of the universities involved approved all procedures for this project.

2.2 Measures and Covariates

Programming Self-Efficacy survey items were adapted for coding courses [68]. The mean of five items is used to represent programming self-efficacy. These items included: I can answer all the questions on a coding class test or exam; I can figure out how to finish a coding class project at home; I can understand information on websites about programming or code information; If a group of students is having a discussion about the code of an assignment I could participate actively; and If I were working on a coding class project I could find useful resources on my own. Participants responded on a 4-point scale (with coding values shown in parentheses): I'm very sure I CANNOT do it (1); I'm somewhat sure I CANNOT do it (2); I'm somewhat sure I CAN do it (3); I'm very sure I CAN do it (4). The scale exhibits internal reliability (Cronbach's α = 0.84).

Past programming experience, as a control variable, was measured with a single survey item: Do you have experience in computer coding? Participants responded No (0) or Yes (1).

Course grade, also a control variable, was collected from instructor provided data and represents the final grade of the student as a percentage.

Intervention condition was identified based on institutional enrollment data coded as control (0) and treatment (1) based on section of enrollment.

Multiple Race/Ethnicity variables were created based upon survey responses. Participants indicated their race/ethnicities in the pre-survey by selecting one or more of the following options: African American/Black, American Indian/Alaska Native; Arab, Middle Eastern or Persian; East Asian (e.g., Chinese, Japanese, Korean, Taiwanese); Southeast Asian (e.g., Vietnamese, Thai, Laotian, Filipino, Malaysian); Indian/Pakistani/Bangladeshi; Other Asian (please specify); Mexican American/Chicano or Mexican; Central American (e.g., Nicaraguan, Honduran); South American; Puerto Rican; Other Latinx (please specify); Native Hawaiian/Pacific Islander; White/Caucasian; Not listed above (please specify); or Prefer not to respond. From these responses, four binary race/ethnicity variables were constructed such that each represented race/ethnicity is coded as 1 when that identity was selected and 0 when that identity was not selected: African American/Black, Latiné (Mexican American/Chicano or Mexican; Central American; South American; Puerto Rican; Other Latinx), White, and Asian (East Asian; Southeast Asian; Indian/Pakistani/Bangladeshi; Other Asian). Note that students could be coded as 1 in multiple race/ethnicity variables. American Indian/Alaska Native; Arab, Middle Eastern or Persian; Not listed above; or Prefer not to respond are not included as additional race/ethnicity variables for analysis due to limited sample sizes.

A binary Gender variable was created using a survey response. Participants answered the question "What is your gender?" by selecting from Man; Woman; Non-binary/gender-queer; Not listed above (please specify); or prefer not to respond. For the gender variable, only men (0) and women (1) are included. Participants who selected non-binary, gender-queer, not listed above, or prefer not to respond are not used in the analyses of gender as the sample sizes are too small for statistical comparison, and grouping these individuals with other genders obscures the unique experiences of and within this group. Alternative analytic methods are needed to better investigate the effects of the intervention on programming self-efficacy within these individuals.

2.3 Limitations

Small sample sizes for Black, Latiné , and intersections of race/ethnicity, gender, and international students limit our ability to deconstruct effects for groups with multiple identities. The small number of gender and some race/ethnicity groups represented in our data drastically limits our ability to test for potential effects for the most minoritized and underrepresented students in engineering. Analysis of intersecting identifies within gender and race/ethnicity would provide understanding of the effectiveness of the intervention. However, given our sample sizes, these analyses were not possible.

2.4 Positionality

As part of a larger research team, the authors are committed to diversity, equity, inclusion, and justice in STEM education. We study the effects of a psychosocial intervention on students who are marginalized and represented at lower rates than the U.S. population in STEM student classroom experiences and outcomes [61]. As academic researchers, our privileged position represents success in the education system we study, critique, and seek to improve. Some of the research team and authors identify as members of the groups targeted by our intervention efforts, others hold positions of privilege based on social and educational experiences. As a group, we are highly educated white men and women and hold our privileged positions in mind as we investigate the experiences and education of undergraduate students. Our expertise includes psychology, engineering, computing education, engineering education, and higher education. Our range of educational and research backgrounds contributes to a diverse set of resources to support the larger research project, and those aspects of it reported here. In addition, we hold the tension between quantitative and qualitative methods as meaningful for our work investigating identities and social experiences in education. As such, we recognize the patterns identified and reported based on quantitative analyses represent probabilities and may not reflect the lived experiences of all students.

2.5 Analytic Strategy

Analyses were conducted with SPSS v26. Descriptive statistics, including means, standard deviations, kurtosis, skewness, and correlation were examined for normality in the study variables. A comparison of means was used to examine significant differences between groups at pre-test for programming self-efficacy to examine equivalency in condition populations, although the later analytic approach was designed to adjust for any possible initial differences.

Rather than examining simple mean differences by condition in programming self-efficacy overall and within specific groups, we use moderation and moderated moderation tests. Examination of mean differences could identify the main effects of the treatment on programming self-efficacy. However, we expect to identify differential effects of the treatment by race/ethnicity and gender such that the treatment is beneficial for some groups and not others. By using moderated moderation analyses, we are able to detect the differences in moderation of the treatment effect by groups within one analysis. The main analysis engaged SPSS PROCESS Model 3 for moderated moderation (Figs. 1 and 2). A series of analyses tested the moderation of the intervention on pre- to post-programming self-efficacy. In addition, the moderation of the treatment effect was tested to determine moderation by race/ethnicity group (Black, White, Latiné and Asian) or binary gender while controlling for international status, course grade, and binary coding experience. To mitigate family-wise error with multiple comparisons, we use the Bonferroni correction for five comparisons to establish the sig-

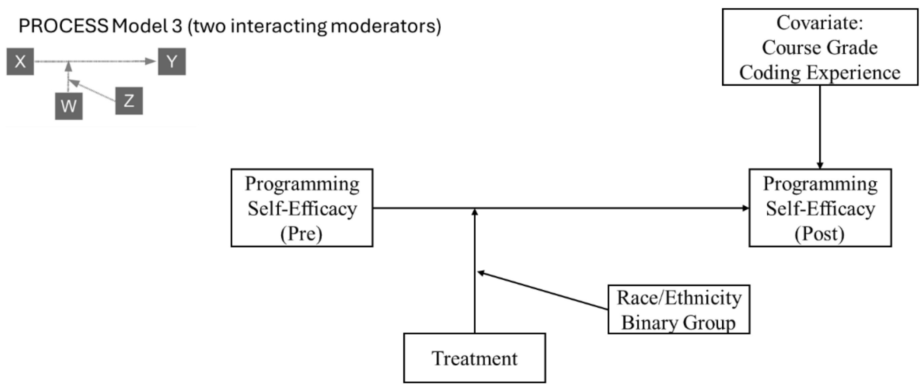

Fig. 1. Moderated moderation of PSE by treatment condition moderated by race/ethnicity group.

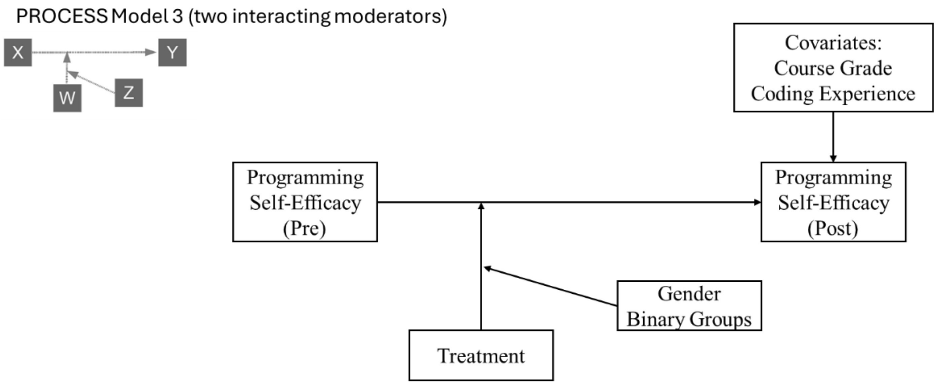

Fig. 2. Moderated moderation of PSE by treatment condition moderated by gender group.

nificance value below 0.01 [69]. For significant interactions, the treatment effect was decomposed and graphed using visualization code generated by PROCESS.

3. Results

Descriptive statistics showed that skewness and kurtosis for the main analytic variable, self-efficacy at pre and post, were within acceptable norms to model the data as normal for maximum likelihood estimators (Table 1). Correlations among the variables were not large enough to cause multicollinearity concerns, while the control variables were sufficiently correlated with self-efficacy to warrant inclusion in the models (Table 1).

Table 2 presents the means by the demographic variables (race/ethnicity, international status,

Table 1. Descriptive Statistics for Programming Self-Efficacy at Pre- and Post-test, Course Grade, and Past Programming Experience, Alongside Correlations Among the Variables

Variables	Mean	SD	Skewness	Kurtosis	1	2	3
1. Programming Self-Efficacy (Pre)	2.94	0.66	–0.65	0.58			
2. Programming Self-Efficacy (Post)	3.32	0.50	–0.62	0.88	0.41***		
3. Course Grade	0.90	0.07	–2.33	9.81	0.06*	0.21***	
4. Past Programming Experience	0.51	0.50			0.40***	0.28***	0.05

Note: * indicates $p < 0.05$; *** indicates $p < 0.001$.

Table 2. Pre-test Programming Self-Efficacy Mean and Chi-square Difference for Race/Ethnicity, Gender, Intervention Condition, and Past Programming Experience Groups with Significance Level

Groups	n	Pre-PSE Mean	$\chi 2$	Course Grade Mean
Race/Ethnicity				
Black or African American	24	2.77		0.90
White	710	2.93		0.91
Latiné	91	2.88		0.90
Asian	285	3.03		0.91
Gender			30.44*	
Women	333	2.81		0.90
Men	701	2.99		0.91
International			24.29	
U.S.	923	2.95		0.91
International	145	2.86		0.91
Intervention Condition			16.81	
Treatment	519	2.94		0.90
Control	550	2.95		0.90
Past Programming Experience			205.09***	
No	520	2.67		0.90
Yes	549	3.20		0.91

Note: * indicates $p < 0.05$; ** indicates $p < 0.01$; *** indicates $p < 0.001$.

gender) as well as by intervention condition, and past programming experience. The mean pre-test PSE was examined for each demographic group to determine if there were significant differences in the pre-test. There were small demographic differences in pre-test PSE. ANOVA tests for the intersection of race/ethnicity and international status and Chi-square tests were used for binary groups. Black/African American, white, and Latiné students did not have significant differences based on international status or gender. Asian students were significantly different for international status ($F(1, 1033) = 6.61$, $p = 0.010$), with international students and women reporting significantly lower pre-PSE on average. Overall, international students were not significantly different from U.S. students (Appendix Table A1). Women have significantly lower pre-test PSE scores on average than did men.

Critically, the intervention conditions were not significantly different on pre-PSE, indicating equivalence in starting conditions. Not surprisingly, Pre-PSE was much higher for those with past programming experience compared to those without past programming experience, highlighting the value of including this as a control variable.

Beginning with RQ1, the intervention did not significantly moderate the pre-PSE to post-PSE overall ($F(917) = 0.12$, $p = 0.7$). Turning to RQ2, the intervention moderated pre-PSE to post-PSE in group analyses with significant moderation in the Black student model, the white student model for All Other (African American/Black, American Indian/Alaska Native; Arab, Middle Eastern or Persian; Asian Native Latiné, Hawaiian/Pacific Islander; White/Caucasian; Not listed above or Prefer not to respond) students, and in the gender model for Women. No significant moderation was found for Latiné, Asian, or international students. In all models, pre-PSE, course grade, and past programming experience significantly predicted post-PSE.

In the Black student model, the interaction of intervention condition and Black race/ethnicity, and PSE by intervention condition and Black race/ethnicity significantly moderated PSE. The intervention condition significantly moderated PSE for Black students in the treatment condition. In the treatment condition, Black students with higher pre-PSE had significantly higher post-PSE, while lower pre-PSE was not affected (Table 3, Fig. 3). The intervention conditions alone did not significantly moderate PSE (Table 3). Similarly, the interaction of PSE and condition, Black race/ethnicity, and interaction of PSE and Black race/ethnicity did not significantly moderate PSE. While All Other participants gained in PSE pre- to post-test, no difference existed between treatment and control (Fig. 3). Black students in the control condition had mixed changes to PSE with lower pre-PSE students increasing PSE, moderate pre-PSE students increasing slightly, and high pre-PSE students decreasing towards the mean for Black students (Fig. 3).

The White model had significant moderation for intervention condition, and interaction of intervention condition and race/ethnicity. In the treatment condition, All Other (African American/Black, American Indian/Alaska Native, Arab, Middle Eastern or Persian, Asian, Latiné, Native Hawaiian/Pacific Islander; Not listed above; or Prefer not to respond) students had significant differences based on condition, and White participants were not different based on intervention condition (Table 3, Fig. 4). While not significant, the gap between treatment and control conditions at pre-test closed for All Other students (African American/Black, American Indian/Alaska Native; Arab, Middle Eastern or Persian; Asian, Latiné, Native

Table 3. Moderation of Programming Self-Efficacy by Intervention Condition Moderated by Race/Ethnicity Comparison Groups

Predictor	β	**p**
Black		
Intervention Condition	–0.05	0.7
PSE*Condition	0.01	0.9
Black	0.53	0.3
PSE*Black	–0.28	0.1
Condition*Black	–2.00	0.009
PSE*Condition*Black	0.81	0.003
Latiné		
Intervention Condition	–0.17	0.2
PSE*Condition	0.04	0.3
Latiné	–0.10	0.8
PSE*Latiné	< 0.00	1.0
Condition*Latiné	0.61	0.2
PSE*Condition*Latiné	–0.15	0.3
Asian		
Intervention Condition	–0.08	0.6
PSE*Condition	0.02	0.6
Asian	–0.28	0.2
PSE*Asian	0.10	0.2
Condition*Asian	–0.07	0.8
PSE*Condition*Asian	0.01	0.9
White		
Intervention Condition	–0.51	0.04
PSE*Condition	0.14	0.08
White	0.01	1.0
PSE*White	0.01	0.9
Condition*White	0.59	0.04
PSE*Condition*White	–0.17	0.08

Note: Standard Errors, t, and 95% confidence intervals are in Appendix A, Tables A2, A3, A4, and A5.

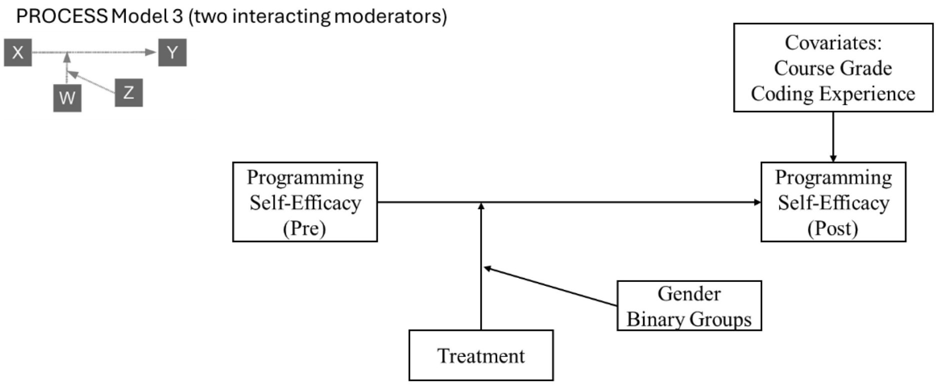

Fig. 3. Interaction of Race/Ethnicity and Condition on the relationship between Programming Self-Efficacy (Pre) to (Post).

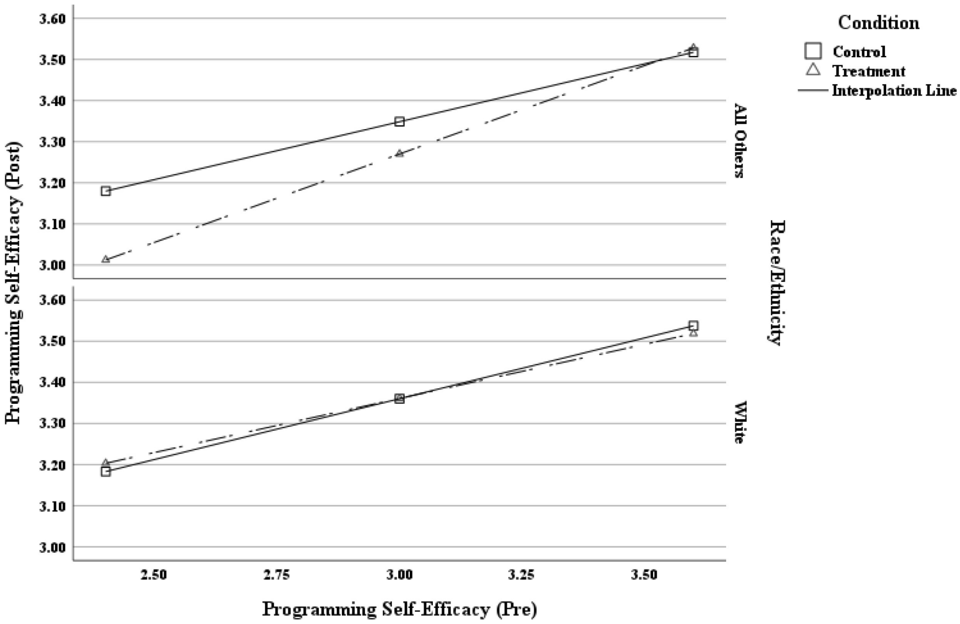

Fig. 4. Interaction of White Race/Ethnicity and Condition on the Relationship between Programming Self-Efficacy (Pre) to (Post).

Hawaiian/Pacific Islander; Not listed above or Prefer not to respond) with the treatment condition students gaining in PSE.

While pre-PSE significantly predicted post-PSE with significant influence of course grade and past programming experience, the Latiné model had no significant treatment effects or interactions (Table 3). We had expected a similar moderated moderation for Latiné students as that for Black students. We reviewed additional descriptive statistics to seek an explanation for why a moderation effect was not detected. Comparing Latiné students to Black students by low/medium/high pre-PSE scores did not identify any meaningful differences between the two groups. For Latiné students, 57% are in the control group, which is proportionate compared to Black 58%. In the treatment group, an equal number (n = 8) are in the low and high categories. In the low category, an equal number (n = 8) are in control (Latiné 15%) and treatment (Black 21%), even though this represents a different percentage. Similarly, in the high category, there are 5 in control (Latiné 10%) and 8 in treatment (Black 21%).

In the Asian model, pre-PSE significantly predicted post-PSE with a significant influence on course grade and past programming experience. Like the Latiné model, no significant treatment effects or interactions were detected (Table 3). The lack of effect for a belonging intervention for Asian students is less surprising given that Asian students are well represented in the student population and engineering generally, and represent more than 25% of the sample. However, cultural differences in beliefs around belonging that emphasize educational achievement in Asian communities [70–73] may also affect the intervention's message and uptake by Asian students.

The gender model identified significant moderation interactions (Table 4). PSE by gender, intervention condition by gender, PSE by intervention

Table 4. Moderation of Programming Self-Efficacy by Intervention Condition Moderated by Gender

Predictor	β	p
Intervention Condition	0.13	0.5
PSE*Condition	–0.06	0.3
Gender	0.37	0.07
PSE*Gender	–0.18	0.008
Condition*Gender	–0.7	0.01
PSE*Condition*Gender	0.27	0.005

Note: Standard Errors, t, and 95% confidence intervals Appendix A, Table A6.

condition, and gender were significant interactions identified in the model. Intervention condition and gender alone were not significant moderators. Women students with higher and moderate pre-PSE had higher post-PSE in the treatment condition, while lower pre-PSE was not affected by the intervention condition (Table 4, Fig. 5). Men in both intervention conditions increased PSE pre-to post-test (Fig. 5).

The moderated moderation models tested identified significant interactions for the intervention condition benefiting Black students, the All-Other students (African American/Black, American Indian/Alaska Native, Arab, Middle Eastern or Persian, Asian, Latiné, Native Hawaiian/Pacific Islander; Not listed above or Prefer not to respond) in the White model, and Women in the gender model. In the Latiné, Asian, and international model, not significant moderations were identified. Pre-PSE, course grade, and past programming experience significantly predicted post-PSE in all models tested.

4. Discussion

4.1 Support of Original Hypotheses

The Ecological Belonging Intervention employed in this study had particularly meaningful effects on PSE for Black students and women. The Black, White, and gender models identify meaningful interactions with the treatment condition to support students' PSE development. However, the strongest effects were for those students who reported higher PSE at pre-test. The implication is that the treatment offers some protection against the struggles encountered in the course. Viewing their struggles as normal allows students to continue to develop PSE. The protective factor then allows for a growth in PSE when students recognize struggle is a normal part of the course and does not indicate a lack of ability or belonging. A similar protective effect is demonstrated in lower PSE students as well in that the PSE does not decrease in response to course struggles.

4.2 Similarity of Results

The use of belonging to improve course outcomes follows similar findings connecting belonging to self-efficacy [51, 74]. Experiences of exclusion limit students' ability to generate belonging and self-efficacy in college classrooms [42, 75]. Experiences that improve students' sense of belonging support self-efficacy [75]. Early college mentorship experiences supported the development of academic self-efficacy and a stronger sense of belonging [76]. While some may focus on course outcomes such as course grades or continued enrollment, impact-

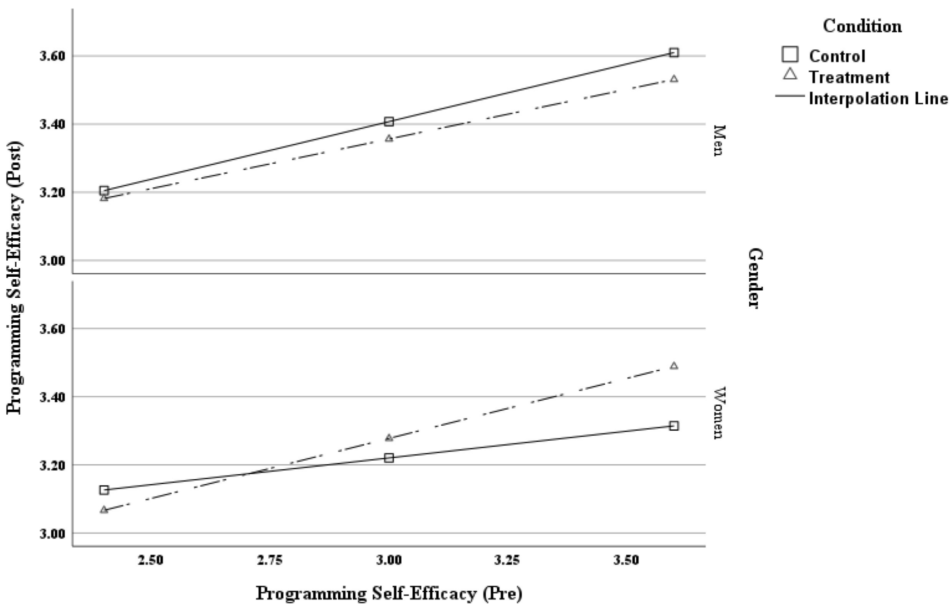

Fig. 5. Interaction of Gender and Condition on the relationship between Programming Self-Efficacy (Pre) to (Post).

ing course-specific self-efficacy represents a meaningful avenue to longer-term goals.

Self-efficacy provides continued support for students' endeavors long after a course grade is posted. Highlighting course-specific self-efficacy over grade performance can support students as they transition into major courses and future careers. While grades can predict future success, self-efficacy in STEM courses offers an alternative predictor of success [21, 23]. As such, self-efficacy may provide longer term support for students when compared to relatively ''short'' term influences of course grades.

4.3 Implications

In-class messages supporting student belonging can target development of self-efficacy without focusing on course grade as an outcome. Focusing on self-efficacy as important for future coursework and success in the major could support more students who enter the course with lower self-efficacy. Further, additional non-college course opportunities to develop programming skills could support students entering engineering without previous programming experience.

Nearly half of our sample did not have past programming experience, which significantly supported PSE in all tested models. Further, the belonging intervention was more effective for students who already had higher PSE at the beginning of the course. While not always available to high school students, adding programming experience prior to enrolling in the first year of engineering coursework could be effective. Through programming bootcamps or bridge programs, high-school or early college experiences could support students in preparation for engineering programming coursework. Computer science and programming bridge programs and workshops introduce high school students to the opportunities in computer science and can provide beginning programming experience [77–79]. Bridge programs improve students' interest in computer science and programming careers while providing exposure to programming and coding [78, 79]. Similar bridge or workshops may be productive for early career engineering and programming students prior to beginning required programming curriculum.

Future research should investigate the nature of differences between groups that may interfere with or alter the effect of belonging interventions for international students, Asian, and Latiné students. The intersections of culture, gender, race/ethnicity, and being an international student complicate the messages of belonging intended to be generated by the intervention. Future research could further develop the belonging messages to better support these students.

5. Conclusions

A sense of belonging is essential for success in college. Perceptions about who can become and engineer and belonging uncertainty based on this stereotype of an engineer as a smart, white man can erode this sense of belonging, especially in fields where women, Black, and Latiné students have been historically underrepresented. Efforts to foster a sense of belonging have effectively enhanced student retention and academic achievement. One such effort aimed at improving the learning environment by illustrating that struggles are a common part of the STEM experience and do not indicate a lack of belonging has shown promise. Moderated mediation analyses demonstrated intervention effects on programming self-efficacy from pre-test to post-test, considering moderation by race/ethnicity (Black, White), and gender (women) suggesting that the intervention was effective in boosting programming self-efficacy among minoritized students. Overall, the ecological belonging intervention positively impacts minoritized students' programming self-efficacy in introductory programming courses.

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Appendix A

Table A1. Moderation of Programming Self-Efficacy by Intervention Condition Moderated by International

Predictor	**B**	**S.E.**	***t***	***p***	**95% CI [LB, UB]**
Programming Self-Efficacy (Pre)	0.25	0.04	6.75	< 0.001	[0.18, 0.32]
Intervention Condition	–0.05	0.15	–0.33	0.744	[–0.33, 0.24]
PSE*Condition	0.01	0.05	0.24	0.810	[–0.08, 0.11]
International	–0.08	0.26	–0.3	0.763	[–0.58, 0.43]
PSE*International	0.01	0.09	0.09	0.927	[–0.16, 0.18]
Condition*International	–0.38	0.37	–1.03	0.304	[–1.12, 0.35]
PSE*Condition*International	0.11	0.13	0.83	0.409	[–0.15, 0.36]
Coding	0.14	0.03	4.24	< 0.001	[0.07, 0.2]
Course Grade	1.50	0.25	6.07	< 0.001	[1.02, 1.99]

Table A2. Moderation of Programming Self-Efficacy by Intervention Condition Moderated by Black

Predictor	β	**S.E.**	***t***	***p***	**95% CI [LB, UB]**
Programming Self-Efficacy (Pre)	0.26	0.03	7.64	< 0.001	[0.19, 0.33]
Intervention Condition	–0.05	0.14	–0.39	0.693	[–0.32, 0.21]
PSE*Condition	0.01	0.05	0.15	0.881	[–0.08, 0.1]
Black	0.53	0.49	1.08	0.282	[–0.44, 1.5]
PSE*Black	–0.28	0.17	–1.65	0.100	[–0.6, 0.05]
Condition*Black	–2.00	0.77	–2.61	0.009	[–3.51, –0.5]
PSE*Condition*Black	0.81	0.28	2.94	0.003	[0.27, 1.36]
Course Grade	1.51	0.25	6.12	< 0.001	[1.02, 1.99]
Coding	0.13	0.03	4.07	< 0.001	[0.07, 0.19]
All Others*Control	0.26	0.03	7.64	< 0.001	[0.19, 0.33]
Black*Control	–0.02	0.16	–0.1	0.924	[–0.34, 0.31]
All Others*Treatment	0.27	0.03	8.17	< 0.001	[0.2, 0.33]
Black*Treatment	0.80	0.22	3.67	< 0.001	[0.37, 1.23]

Table A3. Moderation of Programming Self-Efficacy by Intervention Condition Moderated by Latinx

Predictor	β	**S.E.**	***t***	***p***	**95% CI [LB, UB]**
Programming Self-Efficacy (Pre)	0.25	0.03	7.13	< 0.001	[0.18, 0.32]
Intervention Condition	–0.17	0.14	–1.24	0.215	[–0.45, 0.10]
PSE*Condition	0.04	0.05	0.96	0.340	[–0.05, 0.14]
Latinx	–0.10	0.35	–0.29	0.768	[–0.8, 0.59]
PSE*Latinx	0.00	0.12	0.00	0.999	[–0.24, 0.24]
Condition*Latinx	0.61	0.47	1.29	0.197	[–0.32, 1.54]
PSE*Condition*Latinx	–0.15	0.16	–0.94	0.349	[–0.46, 0.16]
Course Grade	1.56	0.25	6.30	< 0.001	[1.07, 2.04]
Coding	0.13	0.03	4.13	< 0.001	[0.07, 0.19]

Table A4. Moderation of Programming Self-Efficacy by Intervention Condition Moderated by Asian

Predictor	β	**S.E.**	***t***	***p***	**95% CI [LB, UB]**
Programming Self-Efficacy (Pre)	0.23	0.04	6.07	< 0.001	[0.15, 0.3]
Intervention Condition	–0.08	0.15	–0.56	0.578	[–0.38, 0.21]
PSE*Condition	0.02	0.05	0.48	0.630	[–0.08, 0.12]
Asian	–0.28	0.24	–1.17	0.241	[–0.76, 0.19]
PSE*Asian	0.10	0.08	1.25	0.210	[–0.06, 0.25]
Condition*Asian	–0.07	0.33	–0.23	0.820	[–0.72, 0.57]
PSE*Condition*Asian	0.01	0.11	0.08	0.933	[–0.2, 0.22]
Course Grade	0.14	0.03	4.23	< 0.001	[1.03, 2.00]
Coding	1.52	0.25	6.15	< 0.001	[0.07, 0.20]

Table A5. Moderation of Programming Self-Efficacy by Intervention Condition Moderated by White

Predictor	β	**S.E.**	***t***	***p***	**95% CI [LB, UB]**
Programming Self-Efficacy (Pre)	0.24	0.06	4.10	< 0.001	[0.13, 0.36]
Intervention Condition	–0.51	0.24	–2.10	0.036	[–0.99, –0.03]
PSE*Condition	0.14	0.08	1.77	0.077	[–0.02, 0.30]
White	0.01	0.21	0.05	0.958	[–0.4, 0.43]
PSE*White	0.01	0.07	0.08	0.933	[–0.13, 0.14]
Condition*White	0.59	0.29	2.04	0.042	[0.02, 1.17]
PSE*Condition*White	–0.17	0.10	–1.75	0.081	[–0.36, 0.02]
Course Grade	1.51	0.25	6.17	< 0.001	[1.03, 2.00]
Coding	0.14	0.03	4.48	< 0.001	[0.08, 0.21]
All Others*Control	0.24	0.06	4.10	< 0.001	[0.13, 0.36]
White*Control	0.25	0.04	6.34	< 0.001	[0.17, 0.33]
All Others*Treatment	0.39	0.06	6.86	< 0.001	[0.28, 0.50]
White*Treatment	0.22	0.04	5.82	< 0.001	[0.15, 0.30]

Table A6. Moderation of Programming Self-Efficacy by Intervention Condition Moderated by Gender

Predictor	β	**S.E.**	***t***	***p***	**95% CI [LB, UB]**
Programming Self-Efficacy (Pre)	0.30	0.04	7.25	< 0.001	[0.22, 0.39]
Intervention Condition	0.13	0.17	0.75	0.454	[–0.21, 0.47]
PSE*Condition	–0.06	0.06	–1.07	0.285	[–0.17, 0.05]
Gender	0.37	0.20	1.84	0.066	[–0.02, 0.76]
PSE*Gender	–0.18	0.07	–2.65	0.008	[–0.31, –0.05]
Condition*Gender	–0.70	0.28	–2.48	0.013	[–1.25, –0.15]
PSE*Condition*Gender	0.27	0.10	2.83	0.005	[0.08, 0.46]
Course Grade	0.12	0.03	3.64	< 0.001	[0.97, 1.94]
Coding	1.45	0.25	5.88	< 0.001	[0.05, 0.18]
Men*Control	0.30	0.04	7.25	< 0.001	[0.22, 0.39]
Women*Control	0.12	0.05	2.27	0.023	[0.02, 0.23]
Men*Treatment	0.24	0.04	5.93	< 0.001	[0.16, 0.32]
Women*Treatment	0.33	0.05	6.16	< 0.001	[0.23, 0.44]

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