

Collaborative Learning Eliminates the Negative Impact of Gender Stereotypes on Women's Self-Concept

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Abstract

Cultural stereotypes about women's "fit" and ability in technical fields are alive and well. Such cultural beliefs can make their way into women's psyches, and when this happens women's self-conceptions in computing suffer, namely, self-efficacy, sense of belonging, and identification with computing. The current research examines whether collaborative learning methods in the form of study support programs can cancel out the negative relationship between women's endorsement of negative gender stereotypes and their self-conceptions. Longitudinal survey data indicated that participation in collaborative learning activities sever the negative relationship between women's endorsement of gender stereotypes and their professional self-conceptions.

Introduction

Gender stereotypes about women's "fit" and aptitude in technical fields are alive and well. For instance, college students report that they believe men are a better "fit" for quantitative disciplines, such as mathematics and engineering, than women.^{6, 32} The existence of this belief system makes sense, given that students' peer group and faculty role models in quantitative disciplines are indeed predominantly men.^{19, 20} The danger in this beliefs system is that it can bleed into women's self-concept, leading women to question their own aptitude and "fit" in quantitative fields.^{6, 7, 18, 32} Given the dearth of women in quantitative fields and the importance of diversity for creativity in innovative endeavors,^{13, 34} it is troubling to think that talented and motivated women may be shying away from quantitative fields due to their endorsement of cultural stereotypes.

We focus on three self-conceptions in computing, all of which are linked to persistence and success among students: self-efficacy, sense of belonging, and identification with computing. *Self-efficacy* refers to beliefs about one's ability to plan for and execute steps necessary for future success.¹ Research has shown that self-efficacy promotes academic performance and motivation.¹² *A sense of belonging* is defined as the subjective feeling of fitting in and being included as a valued and legitimate member of an academic discipline, and is a known predictor of academic persistence and achievement.^{9, 10, 35} Finally, domain *identification* refers to one's self-definition, or the degree to which one feels that their academic pursuits are an important element of "who they are". As a frame of reference, consider the difference between belonging and identification: whereas belonging reflects one's perceived fit within a group or entity, identification reflects the subjective importance one places on being a member of the group or entity. Domain identification is important because when it is high, positive outcomes are self-relevant and rewarding, thereby motivating achievement.^{8, 21, 22, 29}

Importantly, research indicates that women's engagement in quantitative fields tends to be low when women endorse negative stereotypes about their group. For instance, one line of research indicates that the more women endorse negative stereotypes about their group's ability in the physical sciences, the less they feel like they belong, and the lower their self-efficacy therein.³³ This work indicates that when negative cultural beliefs make their way into women's own personal belief systems, women's commitment to computing may suffer. A substantial body of research also consistently demonstrates that quantitative-related gender stereotypes can arouse *stereotype threat* among women – anxiety about

confirming the negative gender stereotype about women's aptitude, which ironically undermines women's quantitative performance.^{28, 30, 31} Importantly, women's performance is particularly susceptible to stereotype threat when they personally endorse negative gender stereotypes.^{17, 27} This suggests that women who endorse the negative stereotype may be particularly likely to have negative views about their capabilities in quantitative settings.

Given a strong body of research linking stereotype endorsement with women's disengagement in quantitative fields, the question becomes: what might sever this connection? Might there be a pedagogical intervention that promotes engagement among women who are most vulnerable to leaving quantitative fields (i.e. those for whom the negative gender stereotype has made its way into personal beliefs about one's group)? We expect that one way to combat the negative effects of women's stereotypic beliefs on the computing self-concept is to expose women to collaborative learning environments designed to boost aptitude. Two examples of such pedagogical interventions that are increasingly common in computing education are supplemental instruction and pair programming.

Supplemental instruction is a student-led study session where students with questions about course content can convene to discuss and build an understanding of content in a non-threatening, informal setting.⁵ Studies have found participation in supplemental instruction sessions generally builds students' confidence, promotes persistence in challenging courses, and improves course grades.^{5, 23, 36, 38}

Pair programming involves two students working side by side to program simultaneously. This collaborative experience is known to enhance students' confidence in their computer programming abilities, is perceived as more enjoyable than working in isolation, and enhances performance and course completion, which is linked with persistence in computing.^{3, 15, 16, 14}

In addition to their overall effectiveness, collaborative instruction methods, such as supplemental instruction and pair programming, have important advantages in terms of overcoming obstacles faced by underrepresented students in computing. Specifically, these interventions provide a supportive and relatively informal atmosphere, addressing the sense of isolation reported by many underrepresented students,²⁵ and boosting confidence and performance among those students.^{14, 37} Thus, we argue that collaborative learning infrastructure may be particularly useful for women whose personal beliefs increase their risk of leaving computing.

Overview

In the current work, we studied the degree to which women computing majors endorse negative gender stereotypes about women, and how those stereotypic beliefs are related to engagement in computing across time. Our research took place over the course of a year, and involved two time points of data collection. During the first time point, we measured women's stereotypic beliefs about gender aptitude in computing, as well as their self-conceptions in computing (i.e. self-efficacy, belonging, and identification with computing). One year later, we measured women's self-conceptions again, as well as whether women had participated in collaborative learning activities during the past year. We then gauged the link between stereotype endorsement and self-conceptions, and whether that link was severed among women who had participated in collaborative learning. We expected that, consistent with existing research, women's tendency to hold negative beliefs about their group's ability in computing would be negatively associated with their self-efficacy, belonging, and identification with computing.

However, among women who participated in collaborative learning programs, we expected there to be no relationship between negative stereotypic beliefs and self-conceptions in computing.

Participants

Data were collected via an annual survey data collection initiative, which was started in 2011. The data collection method involves collecting data from students at a sample of computing departments across the United States. Departments were originally recruited via stratified random sampling to include roughly equivalent representations of: (1) Ph.D. granting departments; (2) Terminal Master's and Bachelor's granting programs; and (3) programs granting only Bachelor's degrees. Each year, students are invited to complete the survey in exchange for being entered in a raffle to win a \$100 gift card.

The data for the current study were extracted from two datasets that had been collected during the fall 2013 and 2014 academic semesters. At the end of the 2013 survey, students were asked to provide their email addresses so that we could sync up their 2013 data with future data (i.e., 2014 data). Students were told that their email addresses would not be used to recruit them for future surveys. Thus, we did not use email addresses to actively recruit students from the 2013 dataset to participate in the 2014 dataset. In addition to having completed the 2013 and 2014 surveys, students were included in our dataset if they identified as a woman, and had declared a major in computing field. We define "computing field" as either computer science, computing engineering or electrical and computer engineer, computing information systems, or another computing related field including interdisciplinary fields with a strong computing component (e.g., computational biology or digital media). A total of 48 women had completed both surveys and had indicated that they were majoring in a computing field during 2013.

Within our sample of 48 women, 57% were enrolled in Ph.D. granting departments, 11% were enrolled in Terminal Master's granting and Bachelor's granting departments, and 32% were enrolled in Bachelor's granting departments. Of the women in our sample, 2% were African American, 13% were Asian American, 58% were Caucasian, 17% were Latina/o, and 10% identified as Other. The sample consisted of 17% first-year students, 27% second year students, 42% third year students and 14% of students in their fourth year or greater. The distribution of women's demographic characteristics (department type, race/ethnicity, and academic status) in the full 2013 dataset was not statistically significantly different from the distribution of women's demographic characteristics in the sub-sample of women reported on in this paper.

Procedure

Students were invited to complete an online survey via an email invitation sent by their department chair or an administrative staff person in their department. Embedded within the 2013 survey (i.e., Time 1) were questions pertaining to students' gender stereotypic beliefs, self-efficacy in students' computing career trajectory, sense of belonging in the computing community, and identification with computing. The 2014 survey (i.e., Time 2) asked the same questions about self-efficacy, belonging, and identification items, and asked about students' participation in collaborative learning activities during the past year.

Measures

Time 1

Stereotype endorsement: Students rated the degree to which they agreed with the following statements using a (1) *strongly disagree* to (5) *strongly agree* Likert style scale: *I would trust a woman just as much as I would trust a man to solve important computing problems*; and *In my opinion, women are just as talented as men in computing*. Items had good internal reliability (Cronbach's $\alpha = .71$), so we reverse scored and averaged the two items to create an index of students' stereotype endorsement. The aggregate variable ranged from (1) *strongly disagree* to (5) *strongly agree* such that higher values of the scale reflected greater endorsement of gender stereotypes.

Self-efficacy: Students' self-efficacy in computing was assessed via the following prompt and items: *I am confident that I can: complete my undergraduate degree in computing; get admitted to a graduate computing program; find employment in my area of computing interest*, using a scale ranging from (1) *strongly disagree* to (5) *strongly agree*. The Cronbach's α of the three retained items was .61, which is considered adequate. As such, we aggregated these items to form a composite self-efficacy score.

Belonging: Three items assessing belonging were used: *I feel like an outsider in the computing community* (reverse scored); *I feel welcomed in the computing community*; *I do not have much in common with the other students in my computing classes* (reverse scored) using a scale ranging from (1) *strongly disagree* to (5) *strongly agree*. Reliability was good (Cronbach's $\alpha = .77$), so we aggregated them to form a composite belonging measure.

Identification: Two items measured students' identification with computing: *I see myself as a "computing person"*; *I feel like I "belong" in computing*, using a scale ranging from (1) *strongly disagree* to (5) *strongly agree*. Reliability was good (Cronbach's $\alpha = .73$), so items were aggregated to form a composite identification measure. Note that a factor analysis with varimax rotation indicated that the five belonging and identification items loaded on two distinct factors, both with eigenvalues > 1 , and factor loadings $\geq .76$.

Time 2

Collaborative learning: To assess students' involvement with collaborative learning between Time 1 and Time 2, we asked *During the past year, were you involved in study support in computing (e.g., supplemental instruction; pair programming)?* Students indicated either Yes or No to this question.

Self-efficacy, belonging, and identification: The same items used at Time 1 to measure self-conceptions were used again at Time 2. These items had good internal reliability ($\alpha_{\text{Self-efficacy}} = .75$; $\alpha_{\text{Belonging}} = .71$; $\alpha_{\text{Identification}} = .81$) and were aggregated to form their respective constructs.

Results

Preliminary Analysis

Descriptive statistics for Likert style variables measured at Time 1 (*t1*) and Time 2 (*t2*) are displayed in Table 1. Further, we found that 60% of women at *t1* indicated that they had participated in collaborative learning during the past year.

Table 1. Descriptive Statistics for Each Variable at Time 1 (*t1*) and Time 2 (*t2*)

Variable	Mean	Median	SD	Min	Max
Self-Efficacy (<i>t1</i>)	4.24	4.33	0.71	1.33	5.00
Self-Efficacy (<i>t2</i>)	4.35	4.40	0.55	3.20	5.00
Belonging (<i>t1</i>)	3.48	3.67	0.82	1.67	5.00
Belonging (<i>t2</i>)	3.58	3.67	0.82	1.67	5.00
Identification (<i>t1</i>)	3.89	4.00	0.75	2.00	5.00
Identification (<i>t2</i>)	3.86	4.00	0.75	1.00	5.00
Stereotype Endorsement	1.21	1.00	0.52	1.00	3.50

Note. *SD* = standard deviation of the mean. *Min* = minimum value reported.

Max = maximum value reported.

We examined binary correlations between women's stereotype endorsement, their self-conceptions at *t1* and their self-conceptions at *t2*. See Table 2 for correlation coefficients. The correlation coefficients illustrate that all of the self-conception measures were negatively correlated with stereotype endorsement, indicating that perceptions about women's ability and "fit" in computing go hand in hand with women's professional self-conceptions. Specifically, the stronger women's agreement with negative gender stereotypes, the less favorable their self-conceptions.

Table 2. Descriptive Statistics for Each Variable at Time 1 (*t1*) and Time 2 (*t2*)

	2.	3.	4.	5.	6.	7.
1. Stereotype Endorsement (<i>t1</i>)	-0.44**	-0.35*	-0.40**	-0.25+	-0.32*	-0.17
2. Self-Efficacy (<i>t1</i>)	--	0.66***	0.55***	0.41**	0.49***	0.25+
3. Self-Efficacy (<i>t2</i>)	--	--	0.33*	0.37**	0.23	0.36*
4. Belonging (<i>t1</i>)	--	--	--	0.45**	0.34*	0.10
5. Belonging (<i>t2</i>)	--	--	--	--	0.18	0.39**
6. Identification (<i>t1</i>)	--	--	--	--	--	0.46***
7. Identification (<i>t2</i>)	--	--	--	--	--	--

Note. + $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$

Primary Analysis

We expected that stereotype endorsement would negatively predict women's self-conceptions one year later, but that participation in collaborative learning programs would sever this relationship. We utilized two sets of three ordinary least squares regression (OLS) analyses to test our hypotheses; one regression

model assessed self-efficacy at $t2$, a second assessed belonging at $t2$, and a third assessed identification with computing at $t2$.

The first set of regression models examined each self-conception measure at $t2$ (e.g., self-efficacy $t2$) as a function of women's stereotype endorsement at $t1$ and that same self-conception at $t1$ (i.e., self-efficacy $t1$; see Equation 1 for regression equation for the first set of three models). Given that each self-conception at $t1$ was strongly correlated with its respective self-conception at $t2$ (see Table 2), we opted to control for women's $t1$ self-conceptions in our regression models. This allowed us to estimate the effect of stereotype endorsement and collaborative learning on our $t2$ variables, above and beyond individual level factors (e.g., a tendency to have particularly low self-efficacy in general, as measured at $t1$). Thus, the first set of regression models assessed whether stereotype endorsement predicted a self-conception at $t2$, over and above that self-conception at $t1$.

Equation 1: Regression equation for the first set of models

$$\text{Self-conception}_{t2} = \beta_0 + \beta_1 \times \text{Self-conception}_{t1} + \beta_2 \times \text{Stereotype Endorsement}$$

In our second set of models, we added whether or not women had participated in collaborative learning (0 = No; 1 = Yes), and its interaction with stereotype endorsement (see Equation 2 for the regression equation representing the second set of three models). This allowed us to assess whether collaborative learning participation nullified the relationship between stereotype endorsement and $t2$ self-conceptions.

Equation 2: Regression equation for the second set of models

$$\begin{aligned} \text{Self-conception}_{t2} = & \beta_0 + \beta_1 \times \text{Self-conception}_{t1} + \beta_2 \times \text{Stereotype Endorsement} \\ & + \beta_3 \times \text{Collaborative Learning} + \beta_4 \times \text{Stereotype Endorsement} \times \text{Collaborative Learning} \end{aligned}$$

Results for our first set of models revealed that stereotype endorsement had a negative impact on women's self-efficacy, $B = -0.32$, $SE = 0.15$, $p = 0.05$; sense of belonging in computing, $B = -0.48$, $SE = 0.2$, $p = 0.02$; and identification with computing, $B = -0.35$, $SE = 0.19$, $p = 0.07$. Thus, we found that women's tendency to hold negative beliefs about their group's ability in computing predicted lower self-efficacy, belonging, and identification with computing.

Our second set of regression models assessed whether collaborative learning would disrupt the negative impact of women's stereotype endorsement on their self-conceptions in computing. Our second set of models explained more variance in women's self-conceptions at $t2$ than was the case in the first set of models: self-efficacy at $t2$ (Model 1 $R^2 = 46\%$; Model 2 $R^2 = 64\%$), belonging at $t2$ (Model 1 $R^2 = 26\%$; Model 2 $R^2 = 38\%$), and identification with computing at $t2$ (Model 1 $R^2 = 24\%$; Model 2 $R^2 = 35\%$). Note that none of the changes in R^2 was significant. Given the interaction term in the second set of models, the coefficients for collaborative learning and stereotype endorsement reflect the effect of each variable for cases where stereotype endorsement and collaborative learning is equal to zero. As such, in what follows, we only discuss the results of the interaction term for each of our three regression analyses, which are central to our research question.

As expected, each interaction term was significant in each of our models, indicating that the effect of stereotype endorsement on each self-conception at $t2$ depended on whether women had participated in collaborative learning, $ps < .05$. To interpret these interaction effects, we calculated the simple effects

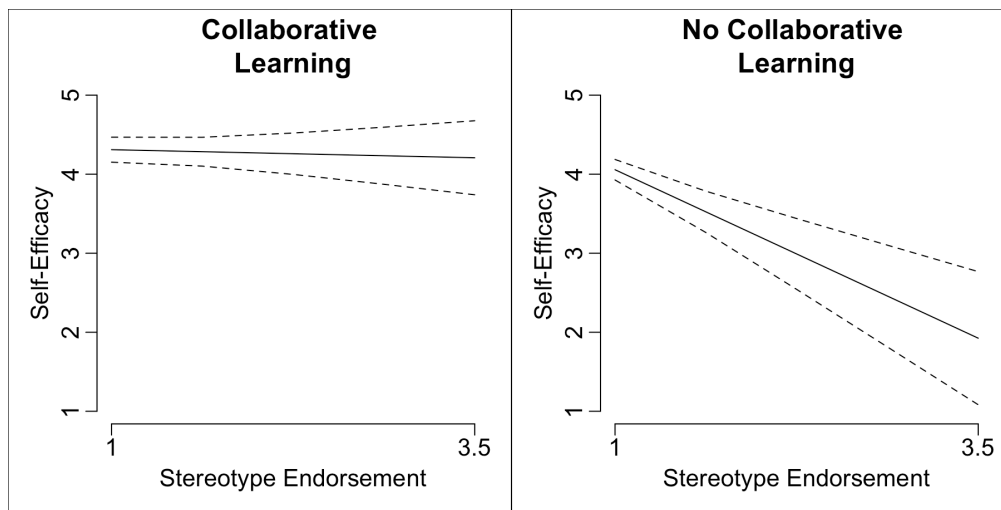
for each regression analysis (see ^{2, 11, 26}), which showed the effect of stereotype endorsement on a given *t2* self-conception measure as a function of whether or not women had participated in collaborative learning. These simple effects are graphically illustrated for all three of our self-conception measures in Figure 1.

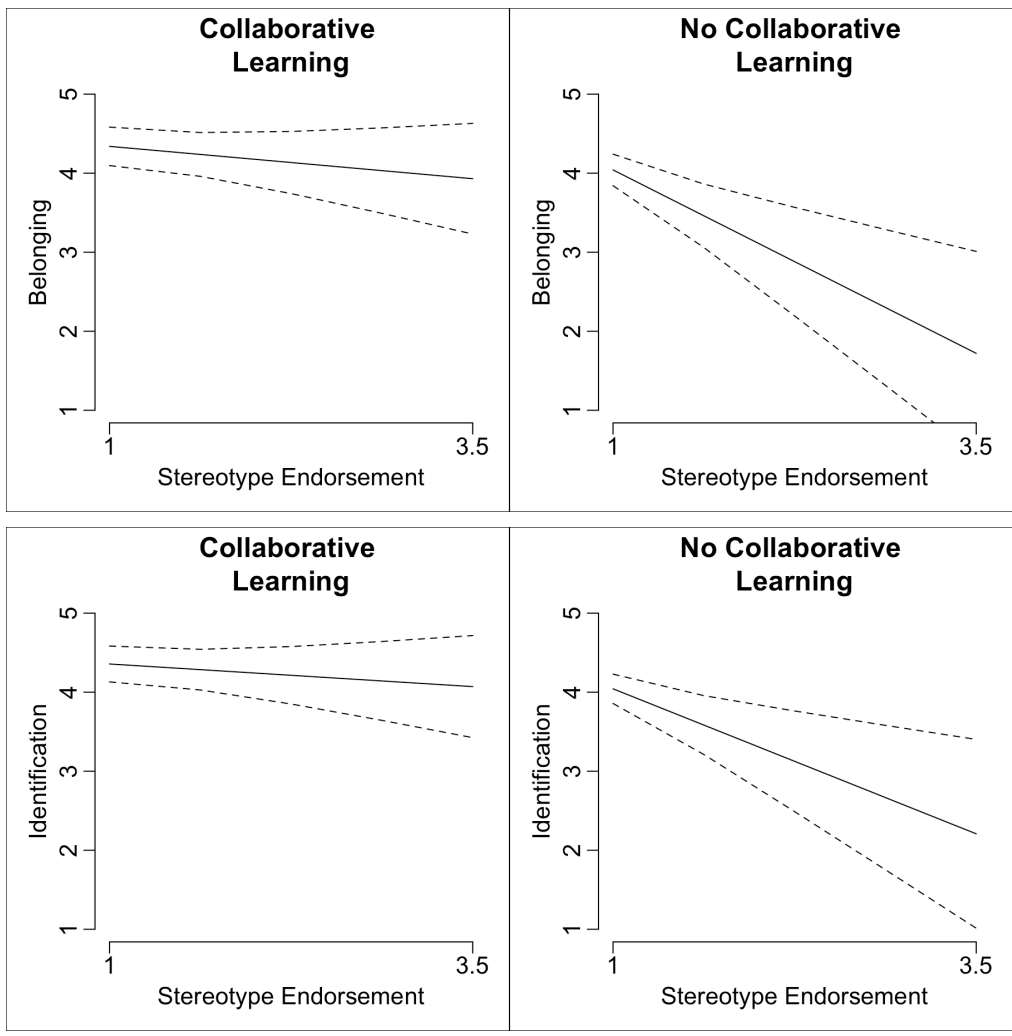
The simple slopes show that, among women who had not participated in collaborative learning, stereotype endorsement negatively predicted each self-conception at *t2*: self-efficacy, $B = -1.33$, $SE = 0.25$, $p < 0.01$, belonging, $B = -1.45$, $SE = 0.38$, $p < 0.01$, and identification with computing, $B = -1.15$, $SE = 0.35$, $p = 0.01$. Thus, these results mimic what we saw in our first set of models. Importantly, among women who had participated in collaborative learning, stereotype endorsement *did not* predict self-efficacy, $B = -0.06$, $SE = 0.14$, $p = 0.66$, belonging, $B = -0.26$, $SE = 0.21$, $p = 0.24$, or identification with computing, $B = -0.18$, $SE = 0.20$, $p = 0.37$.

Post hoc Model Quality Check

One question that arises regarding this analysis is whether women who more strongly endorsed the negative gender stereotype were equally likely to opt in versus not opt in to collaborative learning activities. This is an important question, because a relationship between stereotype endorsement and collaborative learning participation would suggest potential collinearity among the predictors in our models, and require further investigation to ensure accuracy of our inferences. A logistic regression indicated that stereotype endorsement did not predict participating in collaborative learning ($B = .66$, $SE = 0.60$, $p = .27$; i.e., women were equally likely to opt into collaborative learning activities, regardless of their stereotypic beliefs).

Figure 1. Simple Slopes for Stereotype Endorsement





Note. Each panel presents the estimated relationship between stereotype endorsement (x-axis) and a self-conception (y-axis) as a function of whether students participated in collaborative learning. Dashed lines represent the 95% confidence intervals. Consistent with Table 1, the maximum value displayed for stereotype endorsement (x-axis) is 3.5.

Discussion

A recent recruiting advertisement featuring female software engineer Isis Wenger resulted in a barrage of scrutiny on social media concerning whether or not Wenger actually worked as an engineer at the advertised company.⁴ Further, esteemed Nobel Laureate and biochemist Tim Hunt, recently made a public statement that the “trouble with girls” who work in research laboratories is that they “fall in love with you and when you criticize them, they cry”.²⁴ These are but two examples of sexist beliefs about women in science and technology fields, which have occurred as recently as 2015, and have received major media coverage. It is troubling that this sexist belief system persists, because these beliefs can make their way into women’s psyches. Our research indicates that when this happens, women’s self-efficacy, sense of belonging, and identification in computing suffers. Fortunately, our research also indicates that the pernicious effect of stereotype endorsement on women’s self-conceptions can be nullified when women participate in supportive and collaborative educational activities.

Of note, the current work only documented the degree to which supportive education activities in general dampen the pernicious impact of stereotype endorsement on self-conceptions. Future research should explore whether, and to what degree, specific supportive and collaborative pedagogical techniques help promote women's sense of "fit" in computing – particularly those women who have imbibed the negative stereotype about their gender's ability. While we did reference supplemental instruction and pair programming in our measure of women's collaborative learning participation, we did not assess the direct impact of these two types of collaborative learning practices on women's self-conceptions. We also did not assess differential impact, if any, of these two types of collaborative learning on women's self-concept. Future work should pit different types of collaborative learning against each other to measure their differential versus shared benefits on women's engagement in computing.

Note that few women in our sample erred towards gender stereotype endorsement. From an analytic perspective, this means that we worked with small sample sizes after partitioning our data into women with and without collaborative learning experience as a function of stereotype endorsement. Thus, our findings should be interpreted as preliminary, and future research should aim to replicate our findings. Nonetheless, our findings were remarkably consistent across distinct outcome measures, and coalesce with theory outlining the damaging impact of self-stigma on academic engagement and motivation.^{17, 27, 33} Although few women explicitly endorse the negative stereotype about their gender's ability in technical fields, some do hold these negative beliefs. Given that women are in short supply in technical fields like computing and engineering, interventions for small subsets of women are a pedagogical endeavor worthy of pursuit.

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References

- [1] A. Bandura. Self-efficacy: Toward a Unifying Theory of Behavioral Change. *Psychological Review*, 84(2):191–215, 1977.
- [2] D. J. Bauer and P. J. Curran. Probing Interactions in Fixed and Multilevel Regression: Inferential and Graphical Techniques. *Multivariate Behavioral Research*, 40(3):373–400, 2005.
- [3] J. C. Carver, L. Henderson, L. He, J. Hodges, and D. Reese. Increased retention of early computer science and software engineering students using pair programming. *Software Engineering Education Conference, Proceedings*, pp. 115–122, 2007.
- [4] B. Chappell. Sexist Reactions To An Ad Spark #ILookLikeAnEngineer Campaign, 2015.
- [5] H. Congos and N. Schoeps. Does Supplemental Instruction Really Work and What is it Anyway? *Studies in Higher Education*, 18(2):165–177, 1993.
- [6] N. Dasgupta, M. M. Scircle, and M. Hunsinger. Female peers in small work groups enhance women's motivation, verbal participation, and career aspirations in engineering. *Proceedings of the National Academy of Sciences*, pp. 4988–4993, 2015.
- [7] P. G. Davies, S. J. Spencer, D. M. Quinn, and R. Gerhardtstein. Consuming Images: How Television Commercials that Elicit Stereotype Threat Can Restrain Women Academically and Professionally. *Personality and Social Psychology Bulletin*, 28(12):1615–1628, 2002.
- [8] J. D. Finn. Withdrawing From School. *Review of Educational Research*, 59(2):117–142, 1989.
- [9] C. Good, A. Rattan, and C. S. Dweck. Why do women opt out? Sense of belonging and women's representation in mathematics. *Journal of Personality and Social Psychology*, 102(4):700–717, 2012.

- [10] C. Goodenow. The psychological sense of school membership among adolescents: Scale development and educational correlates. *Psychology in the Schools*, 30(1):79–90, 1993.
- [11] C. D. Kam and R. J. Franzese. Modeling and Interpreting Interactive Hypotheses in Regression Analysis: A Refresher and Some Practical Advice. Unpublished manuscript available at: www-personal.umich.edu/franzese/FranzeseKam.Interactions.pdf.
- [12] R. W. Lent, S. D. Brown, and K. C. Larkin. Self-efficacy in the prediction of academic performance and perceived career options. *Journal of Counseling Psychology*, 33:265–269, 1986.
- [13] K. Leung, W. W. Maddux, A. D. Galinsky, and C. Chiu. Multicultural experience enhances creativity: The when and how. *American Psychologist*, 63:169–181, 2008.
- [14] P. Maguire and R. Maguire. Enhancing collaborative learning using pair programming: Who benefits? *Journal of Teaching and Learning in Higher Education*, 6(2), 2014.
- [15] C. McDowell, L. Werner, H. Bullock, and J. Fernald. The impact of pair programming on student performance, perception and persistence. *25th International Conference on Software Engineering, 2003. Proceedings*, pages 602–607, 2003.
- [16] C. McDowell, L. Werner, H. E. Bullock, and J. Fernald. Pair programming improves student retention, confidence, and program quality. *Communications of the ACM*, 49(8):90–95, 2006.
- [17] A. Miyake, L. E. Kost-Smith, N. D. Finkelstein, S. J. Pollock, G. L. Cohen, and T. A. Ito. Reducing the gender achievement gap in college science: a classroom study of values affirmation. *Science*, 330(6008):1234–1237, 2010.
- [18] M. C. Murphy, C. M. Steele, and J. J. Gross. Signaling threat: How situational cues affect women in math, science, and engineering settings. *Psychological Science*, 18(10):879–885, 2007.
- [19] National Science Foundation. Bachelor’s degrees awarded, by race or ethnicity, citizenship, sex, and field: 2012. Table 9-7, 2013.
- [20] National Science Foundation. Integrated Postsecondary Education Data System, Completions Survey, 2002-12. Table 7-2. Doctoral degrees awarded to women, by field: 2002-12, 2013.
- [21] J. W. Osborne. Academics, Self-Esteem, and Race: A Look at the Underlying Assumptions of the Disidentification Hypothesis. *Personality and Social Psychology Bulletin*, 21(5):449–455, 1995.
- [22] J. W. Osborne. Race and academic disidentification. *Journal of Educational Psychology*, 89:728–735, 1997.
- [23] R. V. Pucha and T. T. Utschig. Learning-Centered Instruction of Engineering Graphics for Freshman Engineering Students. *Journal of STEM Education: Innovations & Research*, 13(4):24–34, 2012.
- [24] R. Ratcliffe. Nobel scientist Tim Hunt: female scientists cause trouble for men in labs, 2015.
- [25] K. Redmond, S. Evans, and M. Sahami. A large-scale quantitative study of women in computer science at Stanford University. *Proceeding of the 44th ACM technical symposium on Computer science education - SIGCSE '13*, pp. 439–444, 2013.
- [26] R. L. Rosnow and R. Rosenthal. Definition and interpretation of interaction effects. *Psychological Bulletin*, 105(1):143–146, 1989.
- [27] T. Schmader, M. Johns, and M. Barquissau. The Costs of Accepting Gender Differences: The Role of Stereotype Endorsement in Women’s Experience in the Math Domain. *Sex Roles*, 50:835–850, 2004.
- [28] S. J. Spencer, C. M. Steele, and D. M. Quinn. Stereotype Threat and Women’s Math Performance. *Journal of Experimental Social Psychology*, 35(1):4–28, 1999.
- [29] C. M. Steele. Race and the Schooling of Black Americans. *The Atlantic*, 1992.
- [30] C. M. Steele. A threat in the air. How stereotypes shape intellectual identity and performance. *The American psychologist*, 52(6):613–629, 1997.
- [31] C. M. Steele, S. J. Spencer, and J. Aronson. Contending with Group Image: The Psychology of Stereotype and Social Identity Threat. *Advances in Experimental Social Psychology*, 34:379, 2002.
- [32] J. G. Stout, N. Dasgupta, M. Hunsinger, and M. A. McManus. STEMing the tide: Using ingroup experts to inoculate women’s self-concept in science, technology, engineering, and mathematics (STEM). *Journal of Personality and Social Psychology*, 100(2):255–270, 2011.
- [33] J. G. Stout, T. A. Ito, N. D. Finkelstein, and S. J. Pollock. How Women’s Endorsement of Gendered Science Stereotypes Contributes to the Gender Gap in STEM Participation. Symposium at the annual meeting of the Society for Personality and Social Psychology, 2013.
- [34] A. Thomas. Diversity As Strategy. *Harvard Business Review*, 2004.
- [35] M. Walton and G. L. Cohen. A question of belonging: race, social fit, and achievement. *Journal of Personality and Social psychology*, 92(1):82–96, 2007.
- [36] T. J. Webster and K. a. Y. C. Dee. Supplemental Instruction Integrated Into an Introductory Engineering Course. *Journal of Engineering Education*, 87(4):387–393, 1998.
- [37] L. L. Werner, B. Hanks, and C. McDowell. Pair-programming helps female computer science students. *Journal on Educational Resources in Computing*, 4(1):Article 3, 2004.

[38]L. K. Westin and M. Nordstrom. Supplemental Instruction (SI) - Applied on the course Object-Oriented Programming Methodology. Technical report, Dept. of Computing Science, Umea University, 2003.