Student Perceptions of Their Abilities and Learning Environment in Large Introductory Computer Programming Courses – One Year Later

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Abstract

Over the past 30 years, women completing computer science and computer engineering undergraduate degrees have been a minority compared to their male counterparts. Three obstacles to gender diversity in computer science and computer engineering are: stereotyped traits, perceived abilities, and learning environment. Identifying implicit bias as a component of these obstacles, we implemented a series of activities designed to lessen the impact of implicit bias on our students in large-enrollment introductory computer programming courses. One element of assessing the success of our program is to use entry and exit surveys to gauge the change in students' perceptions of their abilities and learning environment. In particular, we are interested in the difference between men's and women's perceptions of their abilities and the learning environments in these courses.

The initial findings of these entry and exit surveys found that while there are differences between men's and women's responses, the differences were not as great as we had feared. However, due to the relatively large number of responses (1200+) it is possible that even a small difference in, for example, student agreement/disagreement with "I believe that other students in computer programming courses will be welcoming of me" could have a disproportionately large effect on the number of women deciding to major in computer science/computer engineering.

After improving the survey process based on recommendations from the initial study, we embarked on a 5 year program to gather data and assess the gender differences in two sequential large programming courses. Our overarching research question is: Do women and men show a *statistically significant* difference in their perceptions of their abilities and learning environment as measured by self-efficacy, intimidation by programming, and feelings of inclusion?

This paper will present the first set of entry and exit survey results (Fall 2017) analyzed using mixed model ANOVA for repeated measures of questions on self-efficacy, intimidation by programming, and feelings of inclusion. Statistically significant results include: women have lower self-efficacy than men in both courses, and women are more intimidated by programming than men in the second programming course. Although we cannot reject the null hypothesis for any of our three hypotheses regarding these questions, we can still glean useful insight from this data set.

Introduction and Motivation

Over the past 30 years, women completing computer science and computer engineering undergraduate degrees have been a minority compared to their male counterparts.¹ The reasons for this gender gap are complex,² but they can be generalized into the problems of recruitment and retention.

A previous study by the authors³ looked at ways to remove or minimize the impact of three obstacles to gender diversity in the computer science and computer engineering undergraduate programs: stereotyped traits, perceived abilities, and learning environment. Interventions implemented in the first and second programming courses include:

- balanced teaching staff in terms of gender and race (visual representation is critical)
- staff training on implicit bias, stereotype threat, etc.
- various student activities related to implicit bias
- personalized messaging via an electronic coaching system

The obstacles of stereotyped traits, perceived abilities, and adverse learning environment exist for many different social groups. These introductory programming courses are some of the largest engineering classes offered at this institution; as such, they have a wide sphere of influence on the student body. An improved understanding of student experiences in these classes will provide guidance on creating *and sustaining* a welcoming environment for all students.

In our previous research, we asked students for their perceptions of the impact of stereotypes, preconceived notions of ability, and learning environment on their experiences in their programming courses. The difference in responses between women and men were not as large as we had feared at the beginning of the study, and this was encouraging. This may indicate that our efforts to combat implicit bias were partially successful, although since we do not have pre-implicit bias activity data, we cannot be certain. However, the relatively large number of responses (1200+) means it is possible that even a small difference in responses between men and women may be significant.

With this previous study appearing to indicate that the programming courses are not horrible in terms of gender disparity, we turn now towards incremental improvement and longer term trends. This paper addresses three action items from the previous study:

Improvement #1: Continue to administer the surveys and use results to guide future course development and other possible interventions.

Action: We have IRB approval for a 5 year program to assess the success of this program on combating implicit bias.

Improvement #2: Ask demographic information at the end of the entry survey to avoid tainting data with preconceived notions of what the answers should be (stereotype threat).

Action: We moved all demographic-based questions to the end of the survey.

Improvement #3: Analyze the revised surveys more rigorously to determine metrics that are statistically significant.

Action: We have processed the new, revised surveys using mixed model ANOVA.

Recruiting and retaining women and underrepresented minorities requires term-by-term assessment of students' perceptions of the courses. In particular, we chose to focus on indicators for self-efficacy, intimidation by programming, and inclusion. This paper details the entry and exit survey questions used to gather data for these indicators, the analysis results, and our comments on the comparisons between women and men at the beginning of the term and at end of the term.

Methods

We conducted entry and exit surveys to investigate the change in students' perceptions of their abilities and the learning environment in their large introductory programming course. Our hope was that women's perceptions of their abilities and learning environment would show a positive change from the entry survey to the exit survey if our implicit bias activities were effective. Entry and exit surveys already existed for each of the introductory programming courses participating in this study; therefore, we added the questions we needed to the existing surveys. The participants and specific questions added are detailed in the next sections.

Participants

The entry and exit surveys were administered to students in two different large-enrollment computer programming courses at a large, midwestern research university. Course 1 is required of all engineering students and is taken in the first year of study. The students in Course 1 were offered a small amount of extra credit to complete these surveys. Course 2 is the next programming class that students take; it consists of mostly first- and second-year engineering students. Course 2 is required for some majors (computer science, computer engineering, electrical engineering, etc.) but is not required for many other majors, although many non computer/electrical engineering students do take Course 2 in order to become more proficient at programming. The students in Course 2 were required to complete these surveys, which were attached to the existing entry and exit surveys, for course credit. All students were offered the opportunity to opt in or out to the research program without affecting the credit earned in the class. Only students 18 years or older are included in this research.

Design

The surveys were designed to be parallel as much as possible to allow for direct comparison of students' perceptions at the beginning of the course and at the end of the course.

Indicator 1: Self-Efficacy. The definition of success differs widely from student to student, but it primarily revolves around grades. For example, an open-ended question on the entry survey was, "Briefly describe what being SUCCESSFUL in <Course 1> means to you." A word cloud constructed from the students' answers is shown in Fig. 1, and grades are the most commonly referenced definition of success.

Indicator 3: Inclusion. A major aspect of college is peer interaction. Stereotypes certainly play a role in whether a woman will feel welcome and valued in a field,^{14,15} and hence choose to major in that field. Peer encouragement^{16,17} and respect¹⁸ are also important when students choose a major and whether they stay in that major. Therefore, tracking students' feeling of welcome over time will give us an idea of how the inclusiveness of the undergraduate CS program may be changing. If our efforts are effective, then we would see a increase in student's perception of being welcome over the course of the term, with women reporting a larger increase over the course of the term.

Hypothesis 3: Women feel less welcome in our programming courses, as compared to their male peers, but feel more welcome by the end of term.

Table 1 shows the questions used to gather data for these three indicators. The questions as included in the surveys are in Appendix: Sample Survey Questions on page 13.

Table 1: Survey questions used for assessment. Sample questions are included in the Appendix.

Indicator	Entry Survey	Exit Survey	Type
Self-efficacy	How confident are you in your ability to be successful in this course?	Do you think you were successful in this course?	linear scale
Intimidation	I find computer programming intimidating.	I find computer programming intimidating.	linear scale
Inclusion	I believe that other students in computer programming courses will be welcoming of me.	I believe that other students in computer programming courses will be welcoming of me.	linear scale

Analysis

We have two within-subjects repeated measures: the start of term and the end of term. There are two between-subjects: women and men. There are three indicators (self-efficacy, intimidation by programming, and inclusion) and two courses; the survey questions for these indicators are in Table 1. The same survey questions are used for both courses.

After the entry and exit survey data were administered, we first removed any student who was not over 18 and all students who declined to have their answers used for research. Then, the surveys were matched up by student identifier to find the students that took both the entry and the exit surveys. After the matching was done, we removed the student identifiers. From this set of data, we selected those students who self-reported as either men or women. The data set was first graphed as histograms to get a visual sense of the distribution of the answers, then we used SPSS to analyze each data set using a general linear model for repeated measures (mixed model ANOVA).

Results

A summary of the number of responses and response rates is shown in Table 2.

The distribution of responses for each pair of questions are shown in Figs. 2–4. The visual distributions are histograms plotted horizontally with men’s responses on the left and women’s responses on the right. The y axis is labeled with the responses (linear scale or multiple choice); the x axis is the percentage of men or women who selected that response.

The descriptive statistics and marginal mean plots from the mixed model ANOVA are presented in Figs. 5–6. More detailed results are located in the Appendix on page 13.

Table 2: Summary of responses for those students who took *both* the entry and the exit surveys in the Fall 2017 term (September-December 2017).

Course	Enrollment	Total # Respondents	Response Percentage	Women Respondents		Men Respondents	
				#	%	#	%
1	778	232	29.8%	80	34.5%	152	65.5%
2	921	535	58.1%	171	32.0%	364	68.0%
Total	1699	767	45.1%	432	35.8%	775	64.2%

Figure 2: Distribution of responses to the questions, “How confident are you in your ability to be successful in this course?” (Entry Survey) and, “Do you think you were successful in this course?” (Exit Survey)

Figure 3: Distribution of responses to the statement, “I find computer programming intimidating.” Course 1 appears to be divisive for men: male students who were neutral in the beginning of the course grow to either actively like, or actively dislike, programming.

Figure 4: Distribution of responses to the statement, “I believe that other students in computer programming courses will be welcoming of me.”

Descriptive Statistics

	gender	Mean	Std. Deviation	N
entry	Men	4.27	.728	152
	Women	3.81	.765	80
	Total	4.11	.770	232
exit	Men	4.24	.806	152
	Women	4.05	.794	80
	Total	4.18	.805	232

Descriptive Statistics

	gender	Mean	Std. Deviation	N
entry	0	2.93	1.157	152
	1	3.28	1.079	80
	Total	3.05	1.141	232
exit	0	2.93	1.280	152
	1	3.31	1.208	80
	Total	3.06	1.266	232

Descriptive Statistics

	gender	Mean	Std. Deviation	N
entry	0	3.91	.775	152
	1	3.69	.773	80
	Total	3.83	.780	232
exit	0	3.88	.916	152
	1	3.58	.911	80
	Total	3.77	.923	232

Estimated Marginal Means of self-efficacy

Estimated Marginal Means of intimidation

(b) Intimidation by Programming.

Estimated Marginal Means of inclusion

(c) Inclusion.

(a) Self-Efficacy. Between-subjects (gender) is statistically significant.

Figure 5: Summary of mixed model ANOVA results for Course 1. Under “gender”, 0=Men and 1=Women. See Appendix for more details.

Descriptive Statistics

	gender	Mean	Std. Deviation	N
entry	Men	4.01	.877	364
	Women	3.49	.890	171
	Total	3.84	.913	535
exit	Men	3.84	.909	364
	Women	3.46	.862	171
	Total	3.71	.911	535

Descriptive Statistics

	gender	Mean	Std. Deviation	N
entry	Men	2.97	1.159	364
	Women	3.55	1.058	171
	Total	3.15	1.159	535
exit	Men	3.05	1.204	364
	Women	3.35	1.150	171
	Total	3.15	1.194	535

Descriptive Statistics

	gender	Mean	Std. Deviation	N
entry	Men	3.88	.832	364
	Women	3.77	.767	171
	Total	3.85	.813	535
exit	Men	3.86	.953	364
	Women	3.64	.851	171
	Total	3.79	.927	535

Estimated Marginal Means of selfefficacy

Estimated Marginal Means of intimidation

Estimated Marginal Means of inclusion

(a) Self-Efficacy. Between-subjects (gender) is statistically significant.

(b) Intimidation by Programming. Between-subjects (gender) is statistically significant.

(c) Inclusion.

Figure 6: Summary of mixed model ANOVA results for Course 2. Note the reduced range on the vertical axis for the plot of “Inclusion.” See Appendix for more details.

Discussion

Here we offer some discussion of general trends and patterns of this data. We will focus on results that were statistically significant. See the Appendix on page 13 for the significance of within- and between-subjects effects for each course's three indicators.

Self-Efficacy

Visually inspecting the survey results for self-efficacy in Figs. 2, 5a, and 6a, we see that overall men report more self-efficacy than women in both courses and that this difference is statistically significant. This agrees with the large amount of previous research that also finds these differences, and supports the first part of our Hypothesis 1. In Course 1, women show an increase in self-efficacy over the term, but this increase is not statistically significant, therefore we cannot reject the null hypothesis for Hypothesis 1. In Course 2, students of both genders studied show a slight *decrease* in self-efficacy, but again this is not statistically significant. The histogram view in Fig. 2 shows the asymmetry in men's and women's reported self-efficacy (reflected in the marginal means), and also shows how the increase in Course 1's women's self-efficacy comes primarily from those women who were neutral at the beginning of the course feeling more successful at the end of the class.

Intimidation

Visually inspecting the survey results for intimidation by programming in Figs. 3, 5b, and 6b, we see that overall women are more intimidated by programming in both courses, although this difference is statistically significant only for Course 2. Therefore, we cannot reject the null hypothesis for Hypothesis 2. Interestingly, we see that men at the start of Course 2 are, on average, about the same as where they left off at the end of Course 1, but women are on average more intimidated (not statistically significant). We wonder if this means the women in Course 2 are truly more intimidated by programming, or whether they are just more realistic about starting a more difficult programming course! The estimated means for men in Course 1 change very little from the beginning of the term to the end of the term. The histogram view in Fig. 3 gives insight into this apparent non-change – Course 1 appears to be divisive for men in terms of being intimidated by programming. Men who were neutral about programming in the beginning of the term have split, with some being less intimidated by programming and some more intimidated. Women do not report this particular shift.

Inclusion

Visually inspecting the survey results for inclusion in Figs. 4, 5c, and 6c, we do not see much difference between men and women, between the time periods, or between the courses. No effects are statistically significant; therefore, we cannot reject the null hypothesis for Hypothesis 3. Overall, students seem to feel fairly welcome, though the few that do not may well be students that are underrepresented in computer science/engineering. Neither course causes a large decrease in inclusion, which is encouraging.

Conclusions and Recommendations

In this study, we presented the statistical analysis for three indicators of student success (self-efficacy, intimidation by programming, and inclusion) in two sequential large computer programming courses. There are two within-subjects repeated measures: the start of term and the end of term. There are two between-subjects: women and men.

Statistically significant results include: women have lower self-efficacy than men in both courses, and women are more intimidated by programming than men in the second programming course. Although we cannot reject the null hypothesis for any of our three hypotheses, we can still glean useful insight from this data set.

Instructors of large computer programming courses need to continue to support women to overcome obstacles of lower self-efficacy and intimidation by programming. Reinforcing that women “do this” by having female instructors and female teaching assistants is critical, but those women need to be careful not to reinforce existing negative stereotypes of women who program. Diversity in all interpretations of the word is key.

For our own efforts, we plan to continue using these surveys to build more knowledge about our students and inform how we can support them best. For self-efficacy, we plan to calculate the change in response (e.g. from neutral (3) to agree (4)) and do a mixed mode ANOVA on these results to see whether there are large or small increases/decreases in self-efficacy. For intimidation by programming, we plan to identify those students (men and women) who have taken both Course 1 and Course 2 and analyze their responses at the four times (beginning and end of each term) to gain a clearer understanding of how students progress through this programming sequence. For inclusion, we plan to move away from gender differences and begin to look at the inclusion of underrepresented minority students.

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References

- [1] National Center for Education Statistics (NCES). Degrees in computer and information sciences conferred by level of degree and sex of student (table 325.35). *Digest of Education Statistics*, 2013. URL http://nces.ed.gov/programs/digest/d13/tables/dt13_325.35.asp.

- [2] Sylvia Beyer. Why are women underrepresented in computer science? gender differences in stereotypes, self-efficacy, values, and interests and predictors of future cs course-taking and grades. *Computer Science Education*, 24(2-3):153–192, 2014. doi: 10.1080/08993408.2014.963363. URL <http://dx.doi.org/10.1080/08993408.2014.963363>.
- [3] L. K. Alford, M. L. Dorf, and V. Bertacco. Student perceptions of their abilities and learning environment in large introductory computer programming courses. *Proceedings of the 2017 Annual Conference of the American Society for Engineering Education*, 2017.
- [4] A. Rittmayer and M. Beier. Overview: Self-efficacy in stem. *SWE-AWE CASEE Overviews*, 2008.
- [5] S. Gibbs. Computer self-efficacy - is there a gender gap in tertiary level introductory computing classes? *Journal of Applied Computing and Information Technology*, 17(1):91 – 111, 2013. URL http://www.citrenz.ac.nz/jacit/JACIT1701/2013Gibbs_ComputerSelfEfficacy.html.
- [6] J. P. Downey and H. V. Kher. A longitudinal examination of the effects of computer self-efficacy growth on performance during technology training. *Journal of Information Technology Education: Research*, 14:91 – 111, 2015. URL Retrieved from <http://www.jite.org/documents/Vol14/JITEV14ResearchP091-111Downey0828.pdf>.
- [7] F.G. Lopez, R. W. Lent, S. D. Brown, and P. A. Gore. Role of social?cognitive expectations in high school students’ mathematics-related interest and performance. *Journal of Counseling Psychology*, 44(1):44–52, 1997. doi: 10.1037/0022-0167.44.1.44.
- [8] Milagros Sáinz and Jacquelynne Eccles. Self-concept of computer and math ability: Gender implications across time and within ict studies. *Journal of Vocational Behavior*, 80(2):486 – 499, 2012. ISSN 0001-8791. doi: <https://doi.org/10.1016/j.jvb.2011.08.005>. URL <http://www.sciencedirect.com/science/article/pii/S0001879111001126>.
- [9] R. A. Ash, J. L. Rosenbloom, L. Coder, and B. Dupont. *Personality characteristics of established IT professionals I: Big Five personality characteristics*. IGI Global, Hershey, PA, 2006. pp. 983?989.
- [10] Nicole Zarrett, Oksana Malanchuk, Pamela Davis-Kean, and Jacquelynne Eccles. Examining the gender gap in it by race: Young adults decisions to pursue an it career. *Women and information technology: Research on underrepresentation*, pages 55–88, 02 2006.
- [11] S. Katz, J. Aronis, D. Allbritton, C. Wilson, and M. L. Soffa. Gender and race in predicting achievement in computer science. *IEEE Technology and Society Magazine*, 22(3):20–27, Fall 2003. ISSN 0278-0097. doi: 10.1109/MTAS.2003.1237468.
- [12] Susan Haller and Sylvia Beyer. Gender differences and intragender differences in computer science students: are female cs majors more similar to male cs majors or female nonmajors? *Journal of Women and Minorities in Science and Engineering*, 12:337–365, 01 2006.
- [13] Jun He and Lee Freeman. Are men more technology-oriented than women? the role of gender on the development of general computer self-efficacy of college students. *Journal of Information Systems Education*, 21:672, 01 2009.
- [14] Alexandra Fleischmann, Monika Sieverding, Ulrike Hespeneheide, Miriam Weiß, and Sabine C. Koch. See feminine – think incompetent? the effects of a feminine outfit on the evaluation of women’s computer competence. *Computers & Education*, 95:63 – 74, 2016. ISSN 0360-1315. doi: <http://dx.doi.org/10.1016/j.compedu.2015.12.007>. URL <http://www.sciencedirect.com/science/article/pii/S036013151530097X>.
- [15] Jessica L. Cundiff, Theresa K. Vescio, Eric Loken, and Lawrence Lo. Do gender–science stereotypes predict science identification and science career aspirations among undergraduate science majors? *Social Psychology of Education*, 16(4):541–554, Dec 2013. ISSN 1573-1928. doi: 10.1007/s11218-013-9232-8. URL <https://doi.org/10.1007/s11218-013-9232-8>.

- [16] Jill Denner, Linda Werner, Lisa O'Connor, and Jill Glassman. Community college men and women: A test of three widely held beliefs about who pursues computer science. *Community College Review*, 42(4):342–362, 2014. doi: 10.1177/0091552114535624. URL <https://doi.org/10.1177/0091552114535624>.
- [17] Lecia J. Barker, Charlie McDowell, and Kimberly Kalahar. Exploring factors that influence computer science introductory course students to persist in the major. *SIGCSE Bull.*, 41(1):153–157, March 2009. ISSN 0097-8418. doi: 10.1145/1539024.1508923. URL <http://doi.acm.org/10.1145/1539024.1508923>.
- [18] Catherine T. Amelink and Elizabeth G. Creamer. Gender differences in elements of the undergraduate experience that influence satisfaction with the engineering major and the intent to pursue engineering as a career. *Journal of Engineering Education*, 99(1):81–92, 2010. ISSN 2168-9830. doi: 10.1002/j.2168-9830.2010.tb01044.x. URL <http://dx.doi.org/10.1002/j.2168-9830.2010.tb01044.x>.

Appendix: Sample Survey Questions

How confident are you in your ability to be successful in this course?

	1	2	3	4	5	
Not at all confident	☐	☐	☐	☐	☐	I can absolutely do this!

Do you think you were successful in this course? *

	1	2	3	4	5	
Not at all successful	☐	☐	☐	☐	☐	Totally successful

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I find Computer Science intimidating.	☐	☐	☐	☐	☐
I believe that other students in Computer Science will be welcoming of me.	☐	☐	☐	☐	☐

Appendix: Mixed Mode ANOVA Results

The results of the mixed mode ANOVA for all cases is included here. Recall that Course 1 is a required intro to programming course for first year engineering students. For Course 2, the next programming course in the programming sequence. Students are primarily first and second year engineering students. Course 2 is required for some majors, but not required for others (though many non-computer-science/engineering students take this course).

Descriptive Statistics

		Mean	Std. Deviation	N
entry	Men	4.27	.728	152
	Women	3.81	.765	80
	Total	4.11	.770	232
exit	Men	4.24	.806	152
	Women	4.05	.794	80
	Total	4.18	.805	232

Mauchly's Test of Sphericity^a

		Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon ^b		
Within Subjects Effect						Greenhouse-Geisser	Huynh-Feldt	Lower-bound
time		1.000	.000	0	.	1.000	1.000	1.000

Tests of Within-Subjects Effects

Source		Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power ^a
time	Sphericity Assumed	1.169	1	1.169	2.948	.087	.013	2.948	.401
	Greenhouse-Geisser	1.169	1.000	1.169	2.948	.087	.013	2.948	.401
	Huynh-Feldt	1.169	1.000	1.169	2.948	.087	.013	2.948	.401
	Lower-bound	1.169	1.000	1.169	2.948	.087	.013	2.948	.401
time * gender	Sphericity Assumed	1.824	1	1.824	4.600	.033	.020	4.600	.570
	Greenhouse-Geisser	1.824	1.000	1.824	4.600	.033	.020	4.600	.570
	Huynh-Feldt	1.824	1.000	1.824	4.600	.033	.020	4.600	.570
	Lower-bound	1.824	1.000	1.824	4.600	.033	.020	4.600	.570
Error(time)	Sphericity Assumed	91.191	230	.396					
	Greenhouse-Geisser	91.191	230.000	.396					
	Huynh-Feldt	91.191	230.000	.396					
	Lower-bound	91.191	230.000	.396					

a. Computed using alpha = .05

Tests of Between-Subjects Effects

Source		Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power ^a
Intercept		7027.698	1	7027.698	8845.649	.000	.975	8845.649	1.000
gender		11.095	1	11.095	13.965	.000	.057	13.965	.961
Error		182.731	230	.794					

a. Computed using alpha = .05

Estimated Marginal Means of selfefficacy

Figure 7: Results for Course 1: Self-Efficacy. Between-subjects (gender) is statistically significant.

Descriptive Statistics

gender		Mean	Std. Deviation	N
entry	0	2.93	1.157	152
	1	3.28	1.079	80
	Total	3.05	1.141	232
exit	0	2.93	1.280	152
	1	3.31	1.208	80
	Total	3.06	1.266	232

Mauchly's Test of Sphericity^a

intimidation		Epsilon ^b					
Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Greenhouse-Geisser	Huynh-Feldt	Lower-bound
time	1.000	.000	0	.	1.000	1.000	1.000

Tests of Within-Subjects Effects

intimidation		Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power ^a
time	Sphericity Assumed	.051	1	.051	.078	.780	.000	.078	.059
	Greenhouse-Geisser	.051	1.000	.051	.078	.780	.000	.078	.059
	Huynh-Feldt	.051	1.000	.051	.078	.780	.000	.078	.059
	Lower-bound	.051	1.000	.051	.078	.780	.000	.078	.059
time * gender	Sphericity Assumed	.025	1	.025	.038	.845	.000	.038	.054
	Greenhouse-Geisser	.025	1.000	.025	.038	.845	.000	.038	.054
	Huynh-Feldt	.025	1.000	.025	.038	.845	.000	.038	.054
	Lower-bound	.025	1.000	.025	.038	.845	.000	.038	.054
Error(time)	Sphericity Assumed	149.940	230	.652					
	Greenhouse-Geisser	149.940	230.000	.652					
	Huynh-Feldt	149.940	230.000	.652					
	Lower-bound	149.940	230.000	.652					

Tests of Between-Subjects Effects

intimidation Average		Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power ^a
Source									
Intercept		4061.705	1	4061.705	1843.522	.000	.889	1843.522	1.000
gender		13.800	1	13.800	6.264	.013	.027	6.264	.703
Error		506.743	230	2.203					

Estimated Marginal Means of intimidation

Figure 8: Results for Course 1: Intimidation. Under “gender”, 0=men and 1=women. No statistical significance.

Descriptive Statistics

	gender	Mean	Std. Deviation	N
entry	0	3.91	.775	152
	1	3.69	.773	80
	Total	3.83	.780	232
exit	0	3.88	.916	152
	1	3.58	.911	80
	Total	3.77	.923	232

Mauchly's Test of Sphericity^a

inclusion	Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon ^b		
						Greenhouse-Geisser	Huynh-Feldt	Lower-bound
time		1.000	.000	0	.	1.000	1.000	1.000

Tests of Within-Subjects Effects

inclusion		Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power ^a
time	Sphericity Assumed	.554	1	.554	1.186	.277	.005	1.186	.192
	Greenhouse-Geisser	.554	1.000	.554	1.186	.277	.005	1.186	.192
	Huynh-Feldt	.554	1.000	.554	1.186	.277	.005	1.186	.192
	Lower-bound	.554	1.000	.554	1.186	.277	.005	1.186	.192
time * gender	Sphericity Assumed	.166	1	.166	.356	.552	.002	.356	.091
	Greenhouse-Geisser	.166	1.000	.166	.356	.552	.002	.356	.091
	Huynh-Feldt	.166	1.000	.166	.356	.552	.002	.356	.091
	Lower-bound	.166	1.000	.166	.356	.552	.002	.356	.091
Error(time)	Sphericity Assumed	107.412	230	.467					
	Greenhouse-Geisser	107.412	230.000	.467					
	Huynh-Feldt	107.412	230.000	.467					
	Lower-bound	107.412	230.000	.467					

a. Computed using alpha = .05

Tests of Between-Subjects Effects

inclusion		Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power ^a
Average									
Source									
Intercept		5932.295	1	5932.295	6127.812	.000	.964	6127.812	1.000
gender		7.097	1	7.097	7.331	.007	.031	7.331	.769
Error		222.662	230	.968					

a. Computed using alpha = .05

Estimated Marginal Means of inclusion

Figure 9: Results for Course 1: Inclusion. Under “gender”, 0=men and 1=women. No statistical significance.

Descriptive Statistics

	gender	Mean	Std. Deviation	N
entry	Men	4.01	.877	364
	Women	3.49	.890	171
	Total	3.84	.913	535
exit	Men	3.84	.909	364
	Women	3.46	.862	171
	Total	3.71	.911	535

Mauchly's Test of Sphericity^a

selfefficacy		Epsilon ^b						
Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Greenhouse-Geisser	Huynh-Feldt	Lower-bound	
time	1.000	.000	0	.	1.000	1.000	1.000	

Tests of Within-Subjects Effects

Source		Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power ^a
time	Sphericity Assumed	2.381	1	2.381	5.047	.025	.009	5.047	.611
	Greenhouse-Geisser	2.381	1.000	2.381	5.047	.025	.009	5.047	.611
	Huynh-Feldt	2.381	1.000	2.381	5.047	.025	.009	5.047	.611
	Lower-bound	2.381	1.000	2.381	5.047	.025	.009	5.047	.611
time * gender	Sphericity Assumed	1.204	1	1.204	2.551	.111	.005	2.551	.357
	Greenhouse-Geisser	1.204	1.000	1.204	2.551	.111	.005	2.551	.357
	Huynh-Feldt	1.204	1.000	1.204	2.551	.111	.005	2.551	.357
	Lower-bound	1.204	1.000	1.204	2.551	.111	.005	2.551	.357
Error(time)	Sphericity Assumed	251.475	533	.472					
	Greenhouse-Geisser	251.475	533.000	.472					
	Huynh-Feldt	251.475	533.000	.472					
	Lower-bound	251.475	533.000	.472					

a. Computed using alpha = .05

Tests of Between-Subjects Effects

Source		Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power ^a
Intercept		12716.046	1	12716.046	11512.040	.000	.956	11512.040	1.000
gender		47.317	1	47.317	42.837	.000	.074	42.837	1.000
Error		588.745	533	1.105					

a. Computed using alpha = .05

Estimated Marginal Means of selfefficacy

Figure 10: Results for Course 2: Self-Efficacy. Between-subjects (gender) is statistically significant.

Descriptive Statistics

		Mean	Std. Deviation	N
entry	Men	2.97	1.159	364
	Women	3.55	1.058	171
	Total	3.15	1.159	535
exit	Men	3.05	1.204	364
	Women	3.35	1.150	171
	Total	3.15	1.194	535

Mauchly's Test of Sphericity^a

intimidation

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon ^b		
					Greenhouse-Geisser	Huynh-Feldt	Lower-bound
time	1.000	.000	0	.	1.000	1.000	1.000

Tests of Within-Subjects Effects

intimidation

Source		Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power ^a
time	Sphericity Assumed	.752	1	.752	1.120	.290	.002	1.120	.184
	Greenhouse-Geisser	.752	1.000	.752	1.120	.290	.002	1.120	.184
	Huynh-Feldt	.752	1.000	.752	1.120	.290	.002	1.120	.184
	Lower-bound	.752	1.000	.752	1.120	.290	.002	1.120	.184
time * gender	Sphericity Assumed	4.692	1	4.692	6.989	.008	.013	6.989	.751
	Greenhouse-Geisser	4.692	1.000	4.692	6.989	.008	.013	6.989	.751
	Huynh-Feldt	4.692	1.000	4.692	6.989	.008	.013	6.989	.751
	Lower-bound	4.692	1.000	4.692	6.989	.008	.013	6.989	.751
Error(time)	Sphericity Assumed	357.800	533	.671					
	Greenhouse-Geisser	357.800	533.000	.671					
	Huynh-Feldt	357.800	533.000	.671					
	Lower-bound	357.800	533.000	.671					

a. Computed using alpha = .05

Tests of Between-Subjects Effects

intimidation
Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power ^a
Intercept	9710.159	1	9710.159	4832.018	.000	.901	4832.018	1.000
gender	45.187	1	45.187	22.486	.000	.040	22.486	.997
Error	1071.088	533	2.010					

a. Computed using alpha = .05

Estimated Marginal Means of intimidation

Figure 11: Results for Course 2: Intimidation. Between-subjects (gender) is statistically significant.

Descriptive Statistics

		Mean	Std. Deviation	N
entry	Men	3.88	.832	364
	Women	3.77	.767	171
	Total	3.85	.813	535
exit	Men	3.86	.953	364
	Women	3.64	.851	171
	Total	3.79	.927	535

Mauchly's Test of Sphericity^a

inclusion		Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon ^b		
							Greenhouse-Geisser	Huynh-Feldt	Lower-bound
time			1.000	.000	0	.	1.000	1.000	1.000

Tests of Within-Subjects Effects

inclusion		Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power ^a
time	Sphericity Assumed		1.369	1	1.369	3.611	.058	.007	3.611	.475
			1.369	1.000	1.369	3.611	.058	.007	3.611	.475
			1.369	1.000	1.369	3.611	.058	.007	3.611	.475
			1.369	1.000	1.369	3.611	.058	.007	3.611	.475
time * gender	Sphericity Assumed		.628	1	.628	1.658	.198	.003	1.658	.251
			.628	1.000	.628	1.658	.198	.003	1.658	.251
			.628	1.000	.628	1.658	.198	.003	1.658	.251
			.628	1.000	.628	1.658	.198	.003	1.658	.251
Error(time)	Sphericity Assumed		201.974	533	.379					
			201.974	533.000	.379					
			201.974	533.000	.379					
			201.974	533.000	.379					

a. Computed using alpha = .05

Tests of Between-Subjects Effects

inclusion		Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power ^a
Average		Intercept	13368.895	1	13368.895	11829.118	.000	.957	11829.118	1.000
		gender	6.308	1	6.308	5.582	.019	.010	5.582	.655
		Error	602.380	533	1.130					

a. Computed using alpha = .05

Estimated Marginal Means of inclusion

Figure 12: Results for Course 2: Inclusion. Note the reduced range on the vertical axis. No statistical significance.