Making the Implicit Explicit: An Experiment with Implicit Gender Stereotypes and College Major Choice

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This version: January 21, 2026

Abstract

We study whether making college students aware of their implicit gender–STEM stereotypes affects their pursuit of a STEM degree. In a field experiment at a large, selective U.S. university, over 800 undergraduates completed a gender–STEM Implicit Association Test (IAT) and a detailed survey on major preferences and beliefs. Students were randomly assigned to receive feedback about their IAT results or not. Linking survey and IAT data to administrative records on course enrollment and declared major, we find that learning about one's implicit stereotypes increased STEM course-taking and major choice among men, but decreased STEM outcomes among women. The decline for women is concentrated among underrepresented minority, lower-income, and lower-ability students, consistent with stereotype threat mechanisms. The findings highlight that interventions designed to "de-bias" individuals through information can have unintended and asymmetric effects across groups, sometimes reinforcing the very disparities they aim to reduce.

Key Words: STEM, Stereotypes, College Major, Gender, Education
JEL Codes: I21, J16, D83, D91

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The authors thank participants at the University of California Davis, the Pacific Northwest Labor Workshop, and Vassar College for helpful feedback. This study, along with a pre-analysis plan, was pre-registered with the AEA's RCT Registry under ID AEARCTR-0014221.

1 Introduction

Despite decades of research and policy focus, women remain underrepresented in science, technology, engineering, and mathematics (STEM) fields in college and the labor market. Social psychologists have long hypothesized that implicit stereotypes about these traditionally male fields may unconsciously be affecting students' choices in suboptimal ways (Nosek et al., 2002; Kiefer and Sekaquaptewa, 2007; Cvencek et al., 2011; Bian et al., 2017), but have not established a causal relationship. Economists have identified a causal link between implicit stereotypes and discriminatory behavior, but have focused on stereotypes held by others rather than members of the stereotyped group themselves (Glover et al., 2017; Carlana, 2019; Alesina et al., 2024; Martínez, 2025). In this study, we investigate the causal role of students' own implicit stereotypes in explaining gender gaps in college major choice by testing an intervention that makes students aware of their implicit attitudes—which by definition they may not have been aware of.

We conduct a field experiment with close to 900 undergraduates at a selective public university in the U.S. We administer a survey and a gender-STEM Implicit Association Test (IAT) to measure whether and how strongly students implicitly associate STEM fields with men. In an experimental intervention, we randomly provide a subset of students with their IAT results, informing them of their implicit gender-STEM stereotypes and reminding them of the distinction between implicit beliefs and explicit behavior. We then link our survey and IAT results to administrative data at the university to study course-taking behavior and major choice. We supplement administrative data with a second, post-treatment survey and IAT.

Using pre-intervention survey data, we first document that in the absence of any intervention, holding strong male-STEM stereotypes robustly predicts *decreased* interest in STEM for female and non-binary students. For men, male-STEM stereotypes positively predict STEM interest, though the relationship is less robust. This analysis replicates findings from previous descriptive work, including our own (Lane et al., 2007; Cundiff et al., 2013; Owen and Rury, 2025).

In our experimental analysis, we find that informing students of their implicit stereotypes increases STEM outcomes for men, who are 8.6 percentage points (p.p.) more likely to take any STEM courses in the subsequent semester, and take a third more of a STEM course (1.4 credits) on average. We find a positive but non statistically significant increase of 6.3 p.p. on the probability of men declaring a STEM major. The point estimates for female and non-binary students indicate negative effects on STEM course-taking (5.4 p.p. decrease in the extensive margin) and major choice (4.7 p.p. decrease), but are not statistically significant.

Heterogeneity analysis sheds light on the mechanisms behind our main results. We find no heterogeneity by IAT result and therefore the type of message received, suggesting it was the general effect of receiving a message about gender-STEM stereotypes that mattered. However, the effects varied across other subgroups. The intervention discouraged underrepresented minority, lower-income, and less academically prepared women, while having little effect on more advantaged ones. We interpret this result as consistent with stereotype threat, whereby reminding students who may have already felt they didn't belong in STEM reinforced the stereotype.

For male students, we find suggestive evidence of stereotype lift: underrepresented minority men show the largest positive changes in STEM course-taking and major choice. The intervention may have made salient the aspect of their identities (gender) that is positively associated with STEM, rather than the aspect (race) that is not.

Our results suggest a possible tradeoff with stereotype and bias awareness interventions. If a policy goal is to encourage students—especially underrepresented ones—to pursue STEM, then highlighting the beliefs and self-identities that suggest a match with STEM could be effective, but care must be taken not to inadvertently make salient the beliefs and identities that suggest a student doesn't belong.

The rest of the paper is structured as follows. Section 2 discusses related literature; Section 3 provides details about our setting and data; and Section 4 describes the experiment. In Section 5 we present results; in Section 6 we investigate mechanisms behind our results. Section 7 concludes.

2 Related Literature

Determinants of college major choice and gender gaps in STEM are the subject of countless studies in economics and other social sciences. Potential explanations for gender differences include (but are not limited to) mathematical aptitude and comparative advantage (Breda and Napp, 2019; Aucejo and James, 2021; Speer, 2023; Goulas et al., 2024), risk aversion and willingness to compete (Niederle and Vesterlund, 2007; Buser et al., 2014, 2017), interest and relevance of the topics/curriculum (Jensen and Owen, 2000; Owen and Hagstrom, 2021), preference for certain types of jobs and job characteristics (Wiswall and Zafar, 2015, 2018; Kuhn and Wolter, 2022), a lack of female instructors and role models (Bettinger and Long, 2005; Carrell et al., 2010) and the gender composition of peers (Booth et al., 2018; Bostwick and Weinberg, 2022; Calkins et al., 2023). Several interventions have proven successful at encouraging women to pursue male-dominated fields (Li, 2018; Bayer et al., 2019; Porter and Serra, 2020; Patnaik et al., 2024). However, much of the gap remains unexplained (Patnaik et al., 2021; Delaney and Devereux, 2021). We focus on a channel with limited but growing evidence within economics: the role of implicit gender stereotypes.

2.1 Implicit Stereotypes and Behavior

Social scientists have long been interested in the role of stereotypes—overly generalized beliefs about the traits or abilities of different social groups—in shaping behavior and social and economic outcomes (Steele, 1997; Bordalo et al., 2016). *Implicit* stereotypes—those that operate without conscious awareness—can influence judgments, aspirations, and decisions even in the absence of overt prejudice (Greenwald and Banaji, 1995; Bertrand et al., 2005). For example, an employer might aspire to treat workers of different races and ethnicities equally, but may unconciously favor white workers due to implicit bias. A female student may explicitly believe that women and men are equally capable of succeeding in STEM, but implicit gender stereotypes may nevertheless affect her sense of belonging.

A number of observational studies have documented a correlation between implicit gender stereotypes and STEM-related outcomes for female students, including test performance (Nosek et al., 2002; Kiefer and Sekaquaptewa, 2007), math self-concept (Nosek et al., 2002), and STEM interest (Lane et al., 2012; Cundiff et al., 2013; De Gioannis, 2022; Owen and Rury, 2025). However, given the difficulty of finding exogenous variation in implicit stereotypes, this work has yet to establish a causal relationship.

The most convincing causal work on this topic uses plausibly exogenous variation in the implicit stereotypes of others to estimate causal effects on the stereotyped group. For example, workers quasi-randomly assigned to more implicitly biased managers are absent more and perform worse (Glover et al., 2017). Italian middle school girls who are by chance assigned to a more gender-biased teacher perform worse in math, have lower self-confidence, and choose lower academic tracks (Carlana, 2019). A similar study in Peru found that the implicit gender bias of teachers affects students' long-term educational attainment and labor force outcomes (Martínez, 2025).

Our study combines the above strands of the literature and is among the first to study the causal effect of implicit stereotypes held by the stereotyped group itself. Implicit stereotypes about a group an individual identifies with may be even more consequential, and may also be harder to change. On the other hand, people may be more motivated to change behavior that affects them directly.

2.2 De-biasing Interventions

Recognizing the influence of implicit stereotypes on behavior, researchers and policymakers have increasingly turned to interventions designed to reduce or counteract them. Broadly, "de-biasing" efforts seek to weaken the automatic associations that underlie implicit stereotypes or to mitigate their behavioral consequences. Although the idea of changing deep-seated mental associations is conceptually appealing, the empirical evidence on the effectiveness and persistence of such interventions remains mixed.

Early laboratory studies in psychology demonstrated that implicit associations could be temporarily altered through perspective-taking, counter-stereotypical priming, or exposure to counter-stereotypical exemplars (Galinsky and Moskowitz, 2000; Dasgupta and Greenwald, 2001; Blair, 2002). However, subsequent meta-analyses show that these effects often decay rapidly once individuals return to their everyday environments (Lai et al., 2014). The challenge lies not only in changing implicit attitudes but also in translating any such change into sustained behavioral differences. For this reason, we focus on a critical academic decision point—the time when students are registering for courses and choosing their majors—with the motivation that even a short-term effect can have long-term consequences if it happens at a key time. For example, Boring and Philippe (2021) found that informing college students about implicit bias while they filled out teaching evaluations reduced gender discrimination in the evaluations.

The experimental intervention in the present study was partially inspired by Alesina et al. (2024), who study school teachers in Italy. The authors had middle school teachers take an IAT to document implicit bias against immigrant children relative to native ones. They then informed teachers of their results, which they found reduced the extent of grading bias against immigrant students. Apart from the setting (a U.S. university versus an Italian middle school), our experiment differs from Alesina et al. (2024) in one crucial way. That study focused on the effect of implicit stereotypes held by others, rather than by the stereotyped group itself. We study students' own implicit stereotypes, rather than those held by their teachers or others.

The most closely related study—developed independently from our own—studies the relationship between Italian high school students' implicit gender-STEM stereotypes and their interest in STEM fields. De Paola et al. (2025) had students take an IAT, then randomly informed them of their result. They find that for female students with male–STEM implicit associations, the treatment increases their stated interest in STEM; for young women with no implicit stereotype, the effect is negative. Given the different participant ages and contexts, we view our two studies as complementary. However, our study design has several key advantages. De Paola et al. (2025) rely on self-reported outcomes from post-treatment survey data; their main analysis sample includes only 252 observations, with possible non-random selection into the sample. We draw on a much larger sample (N=876) and link students' IAT results to administrative records, allowing us to observe how the treatment affects actual educational decisions rather than relying on self-reported intentions. With no attrition from administrative data, we also have no concerns about treatment-induced selection bias in our experimental estimates.

Our study builds on this growing literature by testing a de-biasing mechanism that targets awareness rather than attitude change. By making students' implicit gender–STEM associations salient through personalized IAT feedback, we investigate whether recognizing one's own implicit stereotypes shifts educational intentions and behaviors. Our IAT and survey data further allow us to disentangle two potential channels: a belief-updating channel, where individuals revise their self-perceptions after learning about hidden biases, and a stereotype-activation channel, where feedback unintentionally reinforces the very associations it aims to diminish. Understanding which mechanism dominates provides insight into the limits of de-biasing interventions and the conditions under which awareness can meaningfully shape behavior.

3 Setting and Data

We study undergraduate students at a large, highly selective public university in the Midwest. Early in the fall 2024 term, we recruited students to participate in our study, which consisted of a baseline and follow-up survey. We incentivized participation with the chance to win one of several \$50 Amazon gift cards if they completed all parts of our initial baseline data collection. We incentivized completion of the follow-up survey with another gift card raffle.

We recruited study participants from two undergraduate populations. The first population consisted of 6,570 students in nine introductory courses in biology, chemistry, computer science, economics, engineering, environmental science, math, and statistics. These courses use an online platform called ECoach, which is a tool designed to provide tailored communication and advice to students in large courses. We coordinated with our research partners at ECoach to use the platform to send recruitment messages to enrolled students. 531 (8%) of the ECoach population participated in some way (measured as completing the consent page of the baseline survey), and 493 (7.5%) are in our final analysis sample (which requires reaching the end of the survey and being randomized to a treatment status).

Our second source of participants comes from the university's office of the registrar, which provided a random sample of 2,500 first-year students who were not enrolled in an ECoach course. We sent recruitment emails directly to these students. Of these invited students, 414 (17%) completed consent and 383 (15%) were randomized into treatment or control. We refer to this as our registrar sample.

In total, 876 students made it to the randomization stage of the study; most of our analyses study intent-to-treat effects on this population.

3.1 University Records

For all students in our sample, we have access to their university administrative records, which we can link to our other data sources. These data contain pre-treatment demographic and academic information, including race, admissions test scores, high school GPA, parent education, family income, and residency status. The data also track each student's complete academic record at the university: courses taken, grades earned, and declared major(s). Our primary outcomes are STEM course-taking (did the student take any STEM courses in a given term, and how many) and officially declared major. We classify courses and majors as STEM using the U.S. Department of Education's Classification of Educational Program (CIP) codes at the two-digit level. We count the following as STEM: natural resources and environmental sciences (CIP = 03), computer science (11), engineering (14), biological sciences (26), math and statistics (27), and physical sciences (40).

We have full information on academic outcomes for all students. Note that although the administrative data contain a student's official major, 80% of our sample are first year students, so a large portion (58%) have no official major. We use intended major from the survey as a secondary outcome (see section 3.2 below). For some students, the data are missing information on pre-college characteristics such as high school GPA and parental education, which are collected during the application process. Some of this information, such as parental education, is self-reported, and some applicants, such as international and transfer students, do not submit certain information.

3.2 Student Surveys

We surveyed students at two points in time: in September (pre-intervention) and again in December (post-intervention). The full survey instruments are included in Appendix B.[1]

The pre-intervention survey first asked students to self-identify their gender, with options for male, female, non-binary, other, or prefer not to say. We use this as our measure of gender, since university records only record legal sex (which must match a government-issued ID).[2] For analyses by gender, we combine female, non-binary, other, and declined students due to the small number in the latter categories, and research suggesting non-binary individuals face particularly high levels of discrimination (Coffman et al., 2024).

To measure intended major, we asked students which major they were most likely to graduate with a degree in, from a list of 16 majors plus a write-in option. We also asked about their second most likely major.[3] In our analysis, we focus on the primary major item. Students are classified as intending a STEM major if they selected or wrote in any of the following as their most likely major: engineering, biology, computer science, math, statistics, data science, neuroscience, environmental science, and other natural sciences.[4]

The remainder of the survey captured beliefs, preferences, and experiences relevant for major choice. We asked students to rate (on a 1-5 Likert scale) how important

[1] The survey is identical to the survey used in Owen and Rury (2025).

[2] Among students who answered our survey item about gender, four percent identified with a gender that did not match the sex recorded in their student record.

[3] If a student was considering a double major, the survey instructed students to distinguish between their "primary" and "secondary" major for the two questions.

[4] These majors were clearly marked as "STEM" majors in the survey, so there was no ambiguity between the participant and the researchers regarding which majors constituted STEM majors or not.

seven different factors were in choosing their major: “Feeling like I’m good at the subject,” “Being engaged with the coursework (while in school),” “Making/having friends or study partners in the major,” “Expected salary (after graduation),” “Work flexibility (after graduation),” “Having a positive impact on society (after graduation), and “Work culture/peers (after graduation).” We also asked them to predict their age-40 salary, conditional on graduating with a degree in their first choice of major; we asked the same question for second choice of major.

We included two items to capture explicitly- (as opposed to implicitly-) held beliefs about gender and college major: students were asked to estimate the proportion of STEM graduates and humanities graduates from the university that they believed were women. (The female STEM graduate belief measure is similar to the stereotype measure used by Kugler et al. (2021).) To measure beliefs about relative ability across fields, we asked them to estimate the high school GPA of graduates who completed a STEM degree, and of those who completed a humanities degree. The final pair of questions asked students for the name and the title (e.g. Ms./Mr./Mx.) of their favorite math or science teacher and of their favorite English or social studies teacher in high school. We use the title to proxy for the presence of pre-college non-male role models by field.

The post-intervention survey repeated a subset of the items from the baseline survey. It again asked students to select their top and second choice of major, and to estimate the proportion of women in STEM and humanities.

3.3 Implicit Association Test

At the end of both surveys, students were directed to a link to take a gender-STEM IAT.[5] Originally developed by social psychologists, the IAT is intended to capture implicit attitudes and beliefs, meaning those that a person might be unaware of but which nevertheless affect judgment and behavior (Greenwald and Banaji, 1995; Greenwald et al., 1998). Researchers have used the IAT to document implicit associations about different racial and ethnic groups (McConnell and Leibold, 2001), genders (Salles et al., 2019), and religions (Rowatt et al., 2005), among other topics. The instrument is premised on the idea that it takes additional time and effort to perform a task that overrides an unconscious stereotype. In practice, the IAT measures speed on a set of word categorization tasks, with scores reflecting relative response time for stereotypical vs. non-stereotypical

[5]The customized IATs we used were programmed and administered by Harvard University’s Project Implicit.

tasks.

The IAT we administer for this paper, the gender-STEM IAT, contains four categories of words: male (boy, uncle, etc.); female (daughter, woman, etc.); STEM (engineering, geology, etc.); and humanities (literature, history, etc.); Appendix Figure C1 includes the full set of words. In each of seven short modules, participants must sort a series of words to the left or right of a screen using keystrokes or touch (the IAT can be completed using a keyboard or touchscreen device). Three of the modules are practice rounds to familiarize participants with the categories and the mechanics of the test. In the four modules used for scoring, participants are asked to either sort male and STEM words to one side and female and humanities words to the other (stereotypical pairing) or male and humanities to one side and female and STEM to the other (non-stereotypical). In total, participants perform 60 stereotypical and 60 non-stereotypical sorting tasks. Screenshots from the gender-STEM IAT can be found in Appendix Figure C2.

The IAT score is based on the average difference in response times between stereotypical versus non-stereotypical sorting tasks. We use the scoring algorithm developed by Greenwald et al. (2003). Though we report raw scores in summarizing IAT results, for most analysis we standardize within our sample, for more easily interpretable magnitudes.

Although the IAT has been a widely used research tool for decades, its validity remains a topic of debate in the social science literature. There are three broad critiques of the IAT and its ability to measure implicit stereotypes. The first is that the test may only weakly predict the discriminatory behaviors it is intended to measure (Blanton et al., 2009). However, a growing body of research has identified meaningful, causal relationships between IAT scores and real-world discriminatory behavior in contexts such as education (Carlana, 2019; Martínez, 2025), hiring (Rooth, 2010), and management (Glover et al., 2017).

The second criticism is that IAT scores can vary over time, reflecting transient individual or environmental factors. We interpret the IAT as a noisy proxy for an latent trait; such noise would tend to reduce any correlations we observe. Our previous descriptive paper on the relationship between IAT and college major choice (Owen and Rury, 2025), along with the current study, provide direct evidence against these first two critiques.

The last critique is that the IAT may be susceptible to manipulation, with participants potentially able to influence their scores once they understand how the test functions. One study (Fiedler and Bluemke, 2005) found that participants could fake their results when explicitly instructed to do so. However, it is not clear whether individuals would attempt to do this unprompted. While we cannot entirely eliminate this possibility, we follow established scoring guidelines (Greenwald et al., 2003) and exclude data from participants with abnormally slow response times, which may indicate attempts at manipulation. We investigate the possibility of treatment-induced manipulation in Section 5.4.

3.4 Course Gradebooks

For a limited number of STEM courses, we also have access to students' exam scores and final course scores through our research partnership with ECoach. For seven of the ECoach courses, we have final scores in numeric format. For six of those courses, we also have post-treatment exam scores. This is a non-random selection of students' courses, but to supplement our main results we examine treatment effects on STEM performance for a subset of our sample.

4 Experiment

Students who made it to the end of the pre-intervention survey were randomized into treatment or control groups, using Qualtrics' randomization tool. We stratified randomization within three gender strata (female, male, or non-binary/other/preferred not to answer). In total, 418 students were assigned to treatment and 458 to control. Randomization status determined the IAT link a student was directed to. Control and treated students were asked to take identical IATs, with one crucial difference: upon completion of the IAT, control students saw a short message thanking them for their participation, while treated students saw a longer debrief page explaining the test and their results.

The customized debrief first informed students (in large, bold text) about the result of their IAT. For example: "Your responses suggest a moderate automatic association for Male with STEM and Female with Humanities." Depending on IAT score, students received one of seven messages: strong, moderate or slight male-STEM association; strong, moderate, or slight female-STEM association; or little to no automatic association. Figure 1 shows the distribution of messages students received.[6] It further explained how this result was determined: "In other words, you were somewhat faster at sorting STEM with Male words and Humanities with Female words than vice versa." The remainder of the

[6]We use the standard thresholds for IAT categories (Greenwald et al., 2003). Raw scores between -0.15 and 0.15 are considered to have little to no association; scores between 0.15 and 0.35 (in absolute value) are slight, 0.35 and 0.65 are moderate, and above 0.65 are strong.

message provided information about what the IAT measures (implicit attitudes or stereotypes) and, crucially, what it does not measure: behavior. Treated students were told that, "Research shows that making people aware of their implicit attitudes (stereotypes) may help them change their behavior to be less in line with the stereotypes. We're hoping that by seeing your results, it will help you make a more objective and unbiased decision about your own academic path, without the influence of unconscious stereotypes." The message ended with a link to resources to learn more about the IAT. Appendix D shows sample treatment messages.

Treated students first saw the intervention text upon completion of the baseline survey and IAT in September. We sent them the same text again via email in November, when spring course registration was about to begin, with the intent of making the information salient at a crucial decision point.

Not all students assigned to treatment clicked on the IAT link or completed the IAT, in which case they never saw the treatment message. Around 80 percent of students actually completed the IAT. We therefore present intent-to-treat results, showing the effect of assignment to treatment.

5 Results

5.1 Descriptive Statistics and Balance

Table 1 summarizes sample characteristics and tests for treatment-control balance. The majority of participants, 63 percent, are female, non-binary, or other gender. 23 percent of control students are a member of an underrepresented minority (Black, Hispanic, or Native), with the remainder white or Asian. By design, most students in the sample (80 percent) are in their first year of college. This is a high-achieving population at a selective college: their average high school GPA was 3.9, and their SAT or ACT math performance put them at the 94th percentile nationally, on average.

Our data on family income are incomplete, with 25.1 percent of control students missing family income information. 28.5 percent of control students have a reported family income less than $100,000, and the remaining 46.4 percent have family income above $100,000. Only 18 percent are first-generation college students, with the majority of students having a college-educated parent. Over half (57 percent) are in-state students, and 6.5 percent are international.

Based on responses to the pre-intervention survey, the majority (60 percent) of students intend to major in a STEM field; 49 percent selected a STEM field as their second choice major.

78 percent of the sample completed the pre-intervention IAT; this means the remaining 22 percent made it to the end of the survey (when randomization occurred) but did not click on or remain on the link to take the IAT. The average student's raw IAT score of 0.28 corresponds to a slight male-STEM association (using the cutoffs established in Greenwald et al. (2003)). As shown in Figure 2, male students have somewhat stronger implicit stereotypes.

The final column of Table 1 shows that none of the differences between treated and control students are statistically significant (tested using a regression of each characteristic on treatment status, with strata fixed effects).

5.2 Descriptive Evidence on Implicit Stereotypes and Major Intent

The current paper was motivated by our previous descriptive work showing that implicit stereotypes as measured by the IAT are strongly predictive of major choice, and in opposite ways for men and women (Owen and Rury, 2025). In the fall of 2023 (a year before the focal study of this paper), we fielded a survey and IAT very similar to the ones described above. We only collected data at one point in time, and did not include any experimental intervention or follow-up. In that study, we found that female students with a one standard deviation higher male-STEM association were 8-10 p.p. *less* likely to intend to major in STEM, while male students were 7-9 p.p. *more* likely, with point estimates varying slightly based on included covariates.

In Table 2, we repeat this analysis using information from the pre-treatment survey and administrative data, which contain nearly identical measures as our previous study. Specifically, we estimate

$$Y_i = \alpha_0 + \alpha_1 FemaleNB_i + \alpha_2 IAT_i + \alpha_3 FemaleNB_i \cdot IAT_i + \boldsymbol{X_i \theta} + \varepsilon_i \tag{1}$$

where Y_i is student i's stated intention to major in STEM (i.e., listing a STEM field as their top choice of major on the survey). $FemaleNB_i$ is an indicator for the student selecting a non-male gender identity in the survey, and IAT_i is standardized IAT score, with higher values indicating stronger male-STEM implicit stereotypes. α_2 and α_3 are the parameters of interest, telling us how implicit stereotypes predict outcomes: α_2 is the increase in Y associated with a one standard deviation increase in IAT score for men, and $\alpha_2 + \alpha_3$ is the equivalent increase for women and NB students. $\boldsymbol{X_i}$ is a vector of student characteristics including race, parental education and income, international status, and pre-college academic preparation (from administrative data), and beliefs, preferences, and high school experiences related to different majors (from the survey).

We replicate our finding in Owen and Rury (2025) that women with stronger implicit stereotypes are less likely to intend to major in a STEM field. A one-standard-deviation increase in IAT score is associated with women being 11 to 12 p.p. less likely to state that they plan to major in STEM. This result is robust to controlling for factors hypothesized to explain gender gaps in major choice, and which might correlate with IAT: academic preparation; preferences for pecuniary and non-pecuniary features of majors and jobs; explicit beliefs about the representation of women in STEM; beliefs about ability and major; and pre-college STEM role models. Men with stronger IAT scores are 4 to 7 p.p. more likely to intend a STEM major. However, the correlation for men is only marginally statistically significant and not robust to all controls. We view this replication effort as largely successful. Implicit stereotypes remain a robust predictor of intended major for non-male students.[7]

The strong correlational evidence that implicit stereotypes may be preventing some women and NB students from pursuing STEM sets up the primary question of this paper, which is if it is possible to break this correlation and encourage underrepresented students to study STEM. In the rest of the paper, we investigate whether our intervention of informing students about implicit stereotypes affected their major choice.

5.3 Treatment Effects on Primary Course-taking and Major Outcomes

By reminding students of the distinction between implicit beliefs and behavior, we hypothesized that the treatment would cause them to make less gender-stereotypical choices,

[7]Though the correlation for male students is weaker and less robust, the point estimates remain in the same ballpark. Several small but significant differences may explain the differing result for male students. In Owen and Rury (2025), we did not collect information on gender identity, and instead relied on the legal sex measure in the administrative data. So we may be comparing slightly different populations of students, and were previously mis-classifying some students as men who identify as women and vice versa. Second, the timing of data collection differed. In Fall 2023, students took the survey and IAT in late November and December. In Fall 2024, pre-intervention data collection occurred in September. The relationship between implicit stereotypes—and in fact the stereotypes themselves—may change over the course of a semester.

i.e., encourage women to study STEM and possibly encourage men to consider non-STEM.

To study the effect of our intervention, we estimate treatment effects using the following equation:

$$Y_i = \beta_0 + \beta_1 Treat_i + \beta_2 FemaleNB_i \cdot Treat_i + \delta_1 Female_i + \delta_2 NB_i + \varepsilon_i \qquad (2)$$

We account for our stratified randomization procedure by controlling for indicators for female and non-binary/other/declined to answer (with men the omitted third strata). For power reasons, we are not able to estimate effects for non-binary students separately. β_1 gives the treatment effect for men, and $\beta_1 + \beta_2$ gives the pooled effect for women and NB students.

Table 3 shows estimated treatment effects on our four primary outcomes: taking any STEM courses, the number of STEM courses, number of STEM credits, and declaration of a STEM major. All are measured in the semester following the intervention, spring 2025. Receiving feedback about their IAT score and implicit stereotypes appears to have encouraged men to take more STEM courses. Treated men were 8.6 p.p. more likely to take any STEM, took a third more of a course, and took 1.4 more STEM credits, on average. The effect on declared STEM major is a positive but insignificant 6.3 p.p. The effects for women and non-binary students, on the other hand, are mostly negative, and none are statistically significant at conventional levels. Women and NB students were 5.4 p.p. less likely to take any STEM due to the treatment and 4.7 p.p. less likely to be declared as a STEM major. The effect on STEM courses and credits are small and insignificant (0.03 and -0.2, respectively).

Overall, it seems that our feedback intervention encouraged men to continue with STEM and possibly discouraged women. This is the opposite of what we intended, as it reinforces the stereotype. Below, we investigate mechanisms by examining additional outcomes and testing for heterogeneity.

5.4 Treatment Effects on Survey and IAT Outcomes

We supplement our analysis with outcomes measured in the post-intervention survey and IAT. Unlike the administrative data, students chose to respond to the follow-up survey and subsequently to take a second IAT; the possibility that the treatment affected the choice to complete the follow-up would threaten validity of estimated treatment effects using these data. In Table 4, we test whether treated students had differential rates of survey and IAT completion. Consistent with our estimation of treatment effects, we do this separately by gender. Treated students were less likely to complete the follow-up survey (8.6 p.p. for men, 2.3 for women and non-binary), though the difference is not statistically significant. Treated men were 10.7 p.p. less likely to take the post-intervention IAT than control men ($p < 0.10$); treated women were a non-statistically significant 4.8 p.p. less likely to take the IAT. For this reason, we consider all of our results using survey data to be suggestive.[8]

To partially account for non-random selection into the sample, in these analyses, we control for the pre-intervention measure of the outcome:

$$Y_{i,post} = \gamma_0 + \gamma_1 Treat_i + \gamma_2 FemaleNB_i \cdot Treat_i + \lambda Y_{i,pre} + \delta_1 Female_i + \delta_2 NB_i + \varepsilon_i \quad (3)$$

where $Y_{i,post}$ is measured in the post-treatment survey or IAT, and $Y_{i,pre}$ is the same measure from the pre-treatment version.

Table 5 shows treatment effects on survey and IAT outcomes. The effects on intended major (columns 1 and 2) are not significant for any gender. However, there are strong effects on students' explicit beliefs (columns 3 and 4). Men updated their beliefs in the direction of believing there are more women in STEM and fewer in humanities; women also revised downward their belief about women in humanities. We note that these beliefs were not incentivized, so we cannot rule out whether these are true changes or reflect experimenter demand effects.

The final column of Table 5 shows effects on IAT scores. Men's average IAT score decreased by around a third of a standard deviation. There is no significant change to women's IAT score.

The negative effect on men's IAT scores—suggesting they show less stereotypical associations due to the treatment—is somewhat at odds with the positive effects on course-taking. We conduct two additional analyses to investigate this seeming contradiction. The first possibility is that since the sample who took both IATs (N=287) is a subset of the full sample (N=876), the inconsistent results from the administrative versus survey

[8] As a test of successful randomization, we also tested for differential "selection" into the *pre*-treatment IAT, which should be orthogonal to treatment since treatment occurred after IAT completion. Treatment-control differences in pre-treatment IAT rates are small (1 p.p.) and not statistically different from zero.

data reflect different populations. In Appendix Table A1, we re-estimate the effects in Table 3, limiting the sample to those for whom we were able to estimate effects on IAT scores. With this much smaller sample, we lose considerable power, but the effects on male students' STEM course-taking are substantially smaller in the IAT sample. Rather than a decrease of 8.6 p.p. in any STEM course-taking and a third of a STEM course in the full sample, this subsample decreases their STEM course-taking by 3.5 p.p. and their number of courses by 0.1. This implies that men who chose not to take the second IAT changed their course-taking more than men who did take it. However, the null-to-positive effects on the subsample still do not align with the decrease in IAT scores, which would predict lower STEM outcomes for men. Thus, even though some men did weaken their implicit association between gender and STEM, they do not appear to be the ones with the largest behavioral changes. It is possible that the men who increased their STEM course-taking the most also updated their implicit stereotypes, but without full data on IAT scores we cannot say more.

The second possibility is that the changes to IAT score for some men reflect social desirability or experimenter demand effects induced by the treatment rather than a change in the underlying association. Although the IAT is designed to minimize these concerns, in theory it is possible to "game" the IAT with enough knowledge of its mechanics (Fiedler and Bluemke, 2005). We can test for this with the IAT meta-data, which includes response times for the underlying tasks. Increased response times by treated relative to control students could indicate attempts at manipulation. We estimate treatment effects on average response time in milliseconds, averaging across the 120 tasks used in scoring (see Appendix C), and controlling for average response time on the pre-treatment IAT. The results, in Appendix Table A2, show that treated men actually *decrease* their response time by 31 milliseconds (3 percent) more than control men, though the change is not statistically significant. Women's response time increases by an insignificant 27 ms. This suggests that manipulation is not responsible for the observed changes to men's IAT scores.

Thus, while the effects on explicit and implicit beliefs indicate some psychological changes for some students, particularly male ones, the non-random selection into these outcomes and inconsistency with administratively observed outcomes complicate interpretation. We leave further investigation to future research.

6 Mechanisms

Our primary finding—that informing students about implicit stereotypes seems to have widened gender gaps—was the opposite of what we hypothesized when designing the experiment. In this section, we leverage additional administrative and survey data to investigate possible explanations.

6.1 Stereotype Threat and Lift

One potential explanation for our unintended results is the well-known phenomena of stereotype threat (Steele, 1997; Spencer et al., 2016) and stereotype lift (Walton and Cohen, 2003). Stereotype threat occurs when the awareness of a stereotype (e.g., girls are not good at math, or science is for men) causes the stereotyped group to perform worse in the relevant domain (such as a math test), out of fear of conforming to the stereotype. Stereotype lift can improve the performance and self-efficacy of the non-stereotyped group. Perhaps by reminding students of and leading them to reflect on stereotypes about gender and STEM, we unintentionally reinforced those stereotypes.

A traditional test of stereotype threat would compare the performance of the stereotyped group on an assessment for those who are and are not reminded of or primed about the stereotype. For example, Black participants might be told a task is measuring "intellectual ability" (Steele and Aronson, 1995), or women might be told that a test produces gender differences (Spencer et al., 1999). Under stereotype threat, Black students and women would do worse when presented with this framing than when the stereotype is not invoked.

Table 6 tests for this by estimating treatment effects on post-treatment exam and final course scores in a select number of STEM courses for which we have gradebook data. Since a single student can take multiple STEM courses, these analyses are at the student-by-course-by-exam level (for exam effects) or at the student-by-course-level (for final course score effects). We estimate effects with and without course fixed effects. The effects on men's performance are consistently very small (less than half a percentage point) and insignificant. For non-male students, there are reasonably sized negative effects on exam scores—between -2.5 and -3 p.p.—but they are not statistically significant. The point estimates are consistent with stereotype threat negatively affecting non-male students' performance, but unfortunately imprecise.

As another test of stereotype threat, we test for treatment effect heterogeneity among groups that might be especially susceptible. Table 7 estimates effects for non-URM (white or Asian) and URM (Black, Hispanic, or Native) men and women separately. Here, we find fairly strong evidence that URM men increased their STEM coursetaking (24.4 p.p. increase in any courses, and 3.3 more credits), while URM women and NB students decreased the likelihood of taking any STEM by 17.6 p.p. None of the results for White and Asian students are statistically different from zero. One interpretation of this is that minority women hold multiple identities (gender and race/ethnicity) that may prime them to feel they don't belong in STEM; being reminded of one of these identities tips them away from an already precarious interest in STEM. For minority men, on the other hand, we reminded them of the aspect of their identity (gender) that is associated with STEM. Perhaps highlighting the male stereotype helps overrule the racial stereotype.

Table 8 divides students by family income (above vs. below $100,000). The negative effects on the extensive margin of STEM appear to be driven by women and NB students from lower income families: an effect of -17 p.p. Other effects for this group are also negative and substantively large (e.g., -8.4 p.p. decrease in declaring a STEM major) but not statistically significant. The effects for men do not differ much by income.

In Table 9, we split the sample by their SAT or ACT math performance. Although the estimates are somewhat imprecise (recall that not all students submitted scores), they suggest that it's the lower-performing women who decreased STEM course-taking and major. The point estimates for above-median women and NB students are all positive (though only the effect on the number of courses is statistically significant). For below-median women, on the other hand, the treatment decreased the extensive margin of STEM courses by 10.6 p.p. ($p < 0.10$); all other effects for this group are negative but statistically insignificant. Like with the results by race, the intervention message may have reinforced doubt about STEM for women who have already received multiple negative signals about belonging in STEM.

Finally, in Table 10 we classify students by their initial intent to major in STEM, measured on the pre-intervention survey. Women who were *not* initially intending to major in STEM were the ones who were discouraged from the field: 13.2 p.p. decrease in any STEM, 0.25 fewer courses, and 0.86 fewer credits.[9]

[9] We also examine heterogeneity by parent education level and class year. We do not detect differences by parent education, though there is some evidence that men with college educated parents were positively affected (Appendix Table A3). We show in Appendix Table A4 that it appears to be first year men and sophomore and above women who changed their STEM course-taking.

As further evidence about which subgroups were affected by the intervention, we do heterogeneity analysis on our STEM exam and course score data. (For these analyses, we include course fixed effects, as in columns 2 and 4 of Table 6.) Tables 11 and 12 find that lower-income women and those with below-median SAT scores performed significantly worse on post-treatment STEM exams and the courses as a whole. The effects on STEM performance by race (Table 13) are less consistent with the rest of our results, showing that White and Asian women performed worse on exams due to the treatment, with positive, insignificant results for URM women. However, we only have scores for a non-random subset of STEM courses, so we do not put too much weight on this one result.

Although the subgroup analyses are somewhat imprecise, taken as a whole they show that women already receiving negative signals about their fitness for STEM—whether related to their race, family background, or academic performance—were discouraged by a treatment that was intended to encourage them. We attribute this somewhat unexpected result to stereotype threat: by reminding them of the existence of the stereotype that STEM isn't for women—even with context and caveats—we may have inadvertently reinforced it. One silver lining is that we seem to have encouraged underrepresented minority men, possibly by highlighting the aspect of their identities that is positively associated with STEM.

6.2 Belief Updating and De-biasing

Thus far, we have considered "treatment" as a single condition, ignoring the fact that students received different messages based on their IAT results (see Figure 1). In this section, we use the variation in feedback to investigate belief updating as another potential mechanism.

In Table 14, we disaggregate results by the specific intervention message students received (or would have received). We group students by whether they implicitly associated male with STEM, female with STEM, or showed no association.[10] We hypothesized the largest results for students who held the stereotypical association, and were thus told that they implicitly associated male with STEM. However, Table 14 shows no clear pattern by type of feedback. The point estimates for men are similar regardless of feedback,

[10] We can only do this analysis for students with a valid pre-intervention IAT score (N=760), not the full sample of 876. Participants were assigned to a treatment status just prior to starting the IAT, but did receive the treatment message until they completed it. Completing the pre-intervention IAT is balanced by treatment status, so the results are internally valid even if they do not generalize to students who chose not to complete an IAT.

and the same is true for women and NB students. We do the same exercise for survey outcomes (Appendix Table A5) and again cannot reject that effects are the same by type of message received.

However, the content of the message may only matter if it contains new information. For some students, their implicit stereotype may be a surprise, contradicting explicit beliefs, and possibly leading them to change their behavior. It is not ex-ante obvious which direction we would expect behavior to change. If we think of IAT results as a signal (i.e., a male-STEM association is a signal that men are in fact associated with STEM), it could push students towards the stereotypical behavior. Students may also view implicit associations as revealing their own unconscious preference for STEM. On the other hand, de-biasing interventions are premised on the idea that by making people aware of a stereotype that was affecting their behavior without their awareness, they will be *less* likely to let it affect their behavior.

To operationalize this concept, we construct a categorical variable that compares participants' explicitly stated gender–STEM beliefs with their measured implicit associations, both from the pre-treatment survey.[11] We first translate respondents' explicit beliefs—elicited as their perceived percentage of women in STEM—into a binary variable indicating whether they believe that women make up at least half of STEM graduates. We then compare this binary belief measure to each participant's implicit association label (male–STEM association, female-STEM, or no association). With two explicit belief categories and three implicit stereotype categories, there are six possible combinations. In Table A6, we estimate treatment effects separately by gender and these six categories. The results are imprecise, and there are no clear patterns in which students change their behavior. Overall we do not find evidence that belief updating is driving our main effects for either gender.[12]

[11]The analysis in the remainder of this section was not pre-specified; readers should consider the following analysis exploratory.

[12]Table A7 performs the same analysis using 40 percent as the cutoff for explicit male-STEM stereotypes instead of 50 percent; 40 is the modal response in the pre-treatment survey, and also roughly the true proportion both at the university and nationally (National Center for Education Statistics, 2024). The results and our conclusion remain unchanged using this definition.

7 Conclusion

Despite historic progress for women in schooling and the labor market, female students remain underrepresented in STEM fields. Previous descriptive work suggests the role implicit stereotypes might play in perpetuating gender gaps (Nosek et al., 2002; Lane et al., 2012; Owen and Rury, 2025). Motivated by other work finding that the influence of implicit stereotypes can be reduced by making them explicit (Alesina et al., 2024), we collected gender-STEM Implicit Association Test results from a sample of college students, then conducted an experiment where we revealed to students their implicit stereotypes.

Our intervention increased STEM course-taking and major choice for male students and had a negative effect for female students, especially underrepresented minority, lower-income, and lower-performing women. We interpret our results as consistent with stereotype threat for women, and stereotype lift for men. We investigate but find no evidence for a belief updating mechanism.

Our results run counter to those of Alesina et al. (2024), who found that informing teachers of their bias towards immigrant students reduced their bias in grading. A key difference is that the focus of that study is teachers and their views towards others, rather than their own identity. The psychological processes regarding implicit beliefs towards others versus the self likely differ, and are worthy of further investigation.

Our findings also differ somewhat from De Paola et al. (2025), who find *negative* effects of a similar intervention on STEM interest for male high school students with the strongest implicit stereotypes. They also find positive effects on female students with strong stereotypes. However, that study, like ours, finds negative effects for female students with no or weak implicit stereotypes, and the positive effect for high-types is not robust to all controls.[13] Differences in setting might explain differences in results. In addition to studying students of a different age, De Paola et al. (2025) intentionally chose a region of Italy with especially traditional gender norms. Our study also has the advantage of a much larger sample size, and administrative data with no concerns of non-random attrition.

There is a growing economics literature on implicit stereotypes and possible inter-

[13] Although De Paola et al. (2025) report in the text that "students with weak or non-existent stereotypes were unaffected" the reported results in Table 13 show negative effects for students with null stereotypes. Furthermore, adding the main plus interaction effects to obtain subgroup effects results in positive or close to zero effects for the high-stereotype female group in most specifications.

ventions to correct them. Although this may be a promising target for reducing gender and other gaps, our findings suggest that researchers should pay close attention to intervention design and participant characteristics, which may interact in important and unexpected ways. Although we have contributed to an already mixed literature about awareness and debiasing, other types of interventions targeting implicit beliefs might be more successful.

This work is relevant for organizations trying to influence individuals' behavior conditional on their beliefs and implicit associations, particularly when they hold stereotypes against a group of which they are a part.

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Exhibits

Table 1: Balance Table

	Control mean	T-C difference
Female, NB, or other gender	0.632	-0.000
		(0.000)
Underrepresented minority	0.230	-0.032
		(0.028)
Race missing	0.045	0.009
		(0.015)
First year student	0.806	0.028
		(0.026)
High school GPA	3.915	0.003
		(0.008)
HS GPA missing	0.072	0.015
		(0.019)
SAT/ACT math percentile	94.029	-0.568
		(0.865)
SAT/ACT missing	0.261	0.017
		(0.030)
Family income <100K	0.285	0.007
		(0.031)
Family income missing	0.251	-0.025
		(0.029)
First-generation college	0.184	0.006
		(0.027)
Parent ed missing	0.014	-0.004
		(0.007)
In-state student	0.572	0.028
		(0.033)
International student	0.065	0.010
		(0.017)
Top major STEM (pre-treatment)	0.597	0.020
		(0.033)
2nd major STEM (pre-treatment)	0.490	0.020
		(0.035)
Completed pre-treatment IAT	0.780	0.011
		(0.028)
Pre-treatment IAT score (raw)	0.278	-0.002
		(0.030)
N	418	876

Notes: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Treatment-control differences are estimated from a regression of the characteristic on a treatment indicator, controlling for randomization strata (male, female, non-binary/ other/ declined to answer). Robust standard errors in parentheses.

Table 2: Pre-Treatment Relationship between IAT Score, Gender, and Intended Major

	Dependent variable: student intends STEM major							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female or NB	-0.151***	-0.148***	-0.103**	-0.106***	-0.103**	-0.109***	-0.106**	-0.095**
	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)	(0.042)	(0.042)	(0.043)
IAT score (std.)	0.070*	0.062*	0.063*	0.056	0.052	0.050	0.048	0.043
	(0.036)	(0.036)	(0.037)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)
Female/NB x IAT	-0.189***	-0.180***	-0.174***	-0.164***	-0.159***	-0.164***	-0.165***	-0.160***
	(0.042)	(0.042)	(0.043)	(0.044)	(0.044)	(0.044)	(0.043)	(0.044)
IAT effect for women/NB	-0.120***	-0.118***	-0.111***	-0.107***	-0.106***	-0.114***	-0.117***	-0.117***
(main effect + interaction)	(0.022)	(0.022)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Demographics?		x	x	x	x	x	x	x
Academic preparation?			x	x	x	x	x	x
Major importance factors?				x	x	x	x	x
Salary beliefs?					x	x	x	x
Explicit gender-major beliefs?						x	x	x
Major ability beliefs?							x	x
Role models?								x
R^2	0.068	0.082	0.157	0.176	0.186	0.191	0.204	0.208
N	689	689	689	689	689	689	689	689

Notes: $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. All measures in this analysis are from the pre-treatment survey or administrative data. Results from a regression of intended STEM major on non-male gender, standardized IAT score, and their interaction. Intended STEM major is based on a survey item asking students the subject they're most likely to major in. More positive IAT scores indicate stronger male-STEM bias. Demographics include race (URM indicator), first year indicator, parent education (college-educated), family income ($\geq$\$100K), and international status. Academic preparation includes SAT/ACT math percentile, high school GPA, and an indicator for taking calculus in high school. Major importance factors are 7 Likert-scale questions, asking the student to indicate, on a scale of 1-5, how important each of seven factors is for selecting their major. Salary beliefs are expected salaries in each of the student's indicated top two majors. Explicit beliefs are the proportion of STEM graduates the student believes are female and the proportion of humanities graduates the student believes are female. Ability beliefs are what the student estimates as the average high school GPA of a STEM graduate, and of a humanities graduate. Role model measures include indicators for a non-male favorite math/science teacher in high school, and a non-male favorite English/social studies teacher. Regression also includes indicators for missing any of the above.

Table 3: Treatment Effects on STEM Course-taking and Major

	Any STEM courses (SP25)	# STEM courses	# STEM credits	Declared STEM major
Treatment effect on men	0.086**	0.342*	1.414**	0.063
	(0.037)	(0.178)	(0.590)	(0.058)
Male control mean	[0.844]	[2.364]	[7.997]	[0.364]
Treatment effect on women/NB	-0.054	0.026	-0.222	-0.047
	(0.035)	(0.127)	(0.402)	(0.036)
Female/NB control mean	[0.799]	[1.977]	[6.580]	[0.269]
N	876	876	876	876

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Treatment effects are estimated from a regression of the outcome on a treatment indicator, an interaction between treatment and non-male gender, and strata dummies (female and non-binary, with male the omitted third strata). All outcomes are measured in Spring 2025 (the semester following the intervention). Robust standard errors in parentheses.

Table 4: Selection into Post-Treatment Survey and IAT

	Completed survey	Completed IAT
Treatment effect on men	-0.086	-0.107*
	(0.059)	(0.055)
Male control mean	[0.474]	[0.370]
Treatment effect on women/NB	-0.023	-0.048
	(0.041)	(0.040)
Female/NB control mean	[0.519]	[0.417]
N	876	876

Notes: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. Treatment effects are estimated from a regression of the outcome on a treatment indicator, an interaction between treatment and non-male gender, and strata dummies (female and non-binary, with male the omitted third strata). Robust standard errors in parentheses. A student is considered to have completed the survey if they answered the first item, about their top choice of major. They are considered to have completed the IAT if they have a valid IAT score.

Table 5: Treatment Effects on Survey Outcomes

	Top choice major STEM	2nd choice major STEM	Prop. belief female STEM	Prop. belief female human.	IAT score (stdz.)
Treatment effect on men	-0.058	-0.026	3.680***	-2.811**	-0.321*
	(0.037)	(0.074)	(1.233)	(1.364)	(0.192)
Male control mean	[0.726]	[0.687]	[40.986]	[60.151]	[0.479]
Treatment effect on women/NB	0.008	-0.026	1.613	-3.027***	-0.123
	(0.037)	(0.051)	(1.001)	(1.126)	(0.128)
Female/NB control mean	[0.613]	[0.550]	[43.750]	[64.132]	[-0.087]
N	422	374	417	421	287

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Treatment effects are estimated from a regression of the outcome on a treatment indicator, an interaction between treatment and non-male gender, and strata dummies (female and non-binary, with male the omitted third strata). These results also control for the pre-treatment equivalent of the outcome (major choice, beliefs, or IAT score). Robust standard errors in parentheses.

Table 6: Treatment Effects on Exam and Course Performance

	Post-treatment exam score (out of 100)		Final course score (out of 100)	
	(1)	(2)	(3)	(4)
Treatment effect on men	-0.03	0.49	-0.28	0.20
	(2.52)	(2.52)	(1.52)	(1.55)
Male control mean	[85.0]	[85.0]	[88.7]	[88.7]
Treatment effect on women/NB	-2.84	-2.61	-0.40	-0.73
	(1.90)	(1.79)	(1.20)	(1.10)
Female/NB control mean	[83.3]	[83.3]	[88.5]	[88.5]
Course FE?	N	Y	N	Y
N	573	573	438	438

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Analysis in Columns 1 and 2 is at the student-by-course-by-exam level; analysis in Columns 3 and 4 is at the student-by-course level. Treatment effects are estimated from a regression of the outcome on a treatment indicator, an interaction between treatment and non-male gender, and strata dummies (female and non-binary, with male the omitted third strata). Outcomes are measured in Fall 2024; exams taken pre-treatment are not included. Regressions also include course fixed effects as indicated. Robust standard errors clustered at the student level in parentheses.

Table 7: Treatment Effects on STEM Course-taking and Major, by Race/Ethnicity

	Any STEM courses (SP25)	# STEM courses	# STEM credits	Declared STEM major
Non-URM (White or Asian)				
Men	0.043	0.221	0.827	0.031
	(0.039)	(0.196)	(0.646)	(0.066)
	[0.883]	[2.558]	[8.696]	[0.400]
Women/NB	-0.021	0.042	-0.186	-0.067
	(0.038)	(0.144)	(0.454)	(0.042)
	[0.807]	[2.079]	[6.950]	[0.297]
URM (Black, Hispanic, or Native)				
Men	0.244***	0.624	3.271**	0.165
	(0.093)	(0.389)	(1.302)	(0.132)
	[0.706]	[1.676]	[5.529]	[0.235]
Women/NB	-0.176**	-0.064	-0.468	0.017
	(0.079)	(0.267)	(0.837)	(0.068)
	[0.774]	[1.645]	[5.371]	[0.177]
N	876	876	876	876

Notes: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Treatment effects are estimated from a regression of the outcome on a 3-way interaction between treatment, non-male gender, and an indicator for underrepresented minority; and strata dummies (female and non-binary, with male the omitted third strata). URM includes Black, Hispanic, and Native students (including multi-racial/ethnic). All outcomes are measured in Spring 2025 (the semester following the intervention). Robust standard errors in parentheses. Control means in brackets.

Table 8: Treatment Effects on STEM Course-taking and Major, by Family Income

	Any STEM courses (SP25)	# STEM courses	# STEM credits	Declared STEM major
Higher income (>100K)				
Men	0.055	0.216	1.107	0.051
	(0.046)	(0.247)	(0.805)	(0.082)
	[0.886]	[2.608]	[8.614]	[0.405]
Women/NB	0.031	0.081	0.193	-0.028
	(0.053)	(0.191)	(0.623)	(0.054)
	[0.748]	[1.913]	[6.417]	[0.261]
Lower income (<100K)				
Men	0.069	0.347	1.130	0.010
	(0.081)	(0.345)	(1.163)	(0.115)
	[0.829]	[2.114]	[7.486]	[0.400]
Women/NB	-0.168***	-0.151	-0.851	-0.084
	(0.061)	(0.231)	(0.693)	(0.062)
	[0.857]	[2.036]	[6.607]	[0.262]
N	666	666	666	666

Notes: $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Treatment effects are estimated from a regression of the outcome on a 3-way interaction between treatment, non-male gender, and an indicator for family income under $100,000; and strata dummies (female and non-binary, with male the omitted third strata). Students with unknown family income excluded from this analysis. All outcomes are measured in Spring 2025 (the semester following the intervention). Robust standard errors in parentheses. Control means in brackets.

Table 9: Treatment Effects on STEM Course-taking and Major, by Quantitative Test Score

	Any STEM courses (SP25)	# STEM courses	# STEM credits	Declared STEM major
Above median SAT/ACT math				
Men	0.022	0.330	0.985	0.063
	(0.044)	(0.238)	(0.781)	(0.081)
	[0.910]	[2.603]	[9.096]	[0.423]
Women/NB	0.049	0.444**	0.784	0.010
	(0.047)	(0.216)	(0.707)	(0.077)
	[0.875]	[2.325]	[8.300]	[0.400]
Below median				
Men	0.090	-0.135	0.626	0.055
	(0.066)	(0.324)	(1.057)	(0.106)
	[0.851]	[2.340]	[7.638]	[0.298]
Women/NB	-0.106*	-0.111	-0.517	-0.064
	(0.055)	(0.201)	(0.626)	(0.055)
	[0.817]	[1.942]	[6.327]	[0.250]
N	634	634	634	634

Notes: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Treatment effects are estimated from a regression of the outcome on a 3-way interaction between treatment, non-male gender, and an indicator for below-median test score; and strata dummies (female and non-binary, with male the omitted third strata). Test score is measured as the percentile on the math section of the SAT or ACT, or the average of the two if a student took both. The median is calculated within the analysis sample. Students with missing test scores are excluded from this analysis. All outcomes are measured in Spring 2025 (the semester following the intervention). Robust standard errors in parentheses. Control means in brackets.

Table 10: Treatment Effects on STEM Course-taking and Major, by Initial Major Intent (Top Choice Major)

	Any STEM courses (SP25)	# STEM courses	# STEM credits	Declared STEM major
Top choice major STEM pre-treatment				
Men	0.009	0.153	0.653	-0.003
	(0.017)	(0.178)	(0.567)	(0.071)
	[0.980]	[2.971]	[10.275]	[0.549]
Women/NB	0.015	0.288**	0.428	-0.085
	(0.024)	(0.147)	(0.448)	(0.055)
	[0.946]	[2.633]	[8.986]	[0.476]
Top choice major non-STEM pre-treatment				
Men	0.181*	0.261	1.293	0.062
	(0.104)	(0.291)	(0.919)	(0.043)
	[0.569]	[1.176]	[3.520]	[0.000]
Women/NB	-0.132**	-0.254*	-0.864*	0.012
	(0.061)	(0.152)	(0.444)	(0.014)
	[0.615]	[1.154]	[3.556]	[0.009]
N	874	874	874	874

Notes: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Treatment effects are estimated from a regression of the outcome on a 3-way interaction between treatment, non-male gender, and an indicator for top choice major STEM; and strata dummies (female and non-binary, with male the omitted third strata). Major intent is measured in the pre-treatment survey. All outcomes are measured in Spring 2025 (the semester following the intervention). Robust standard errors in parentheses. Control means in brackets.

Table 11: Treatment Effects on Exam and Course Performance, by Family Income

	Exam score (out of 100)	Final course score (out of 100)
Higher income (>100K)		
Men	-0.593	-1.669
	(2.442)	(1.651)
	[89.333]	[91.147]
Women/NB	-1.362	-0.059
	(2.200)	(1.379)
	[84.811]	[88.533]
Lower income (<100K)		
Men	6.521	4.406
	(6.720)	(3.735)
	[75.377]	[83.154]
Women/NB	-7.829**	-4.910**
	(3.250)	(2.093)
	[82.264]	[88.975]
N	449	339

Notes: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Analysis in Column 1 is at the student-by-course-by-exam level; analysis in Column 2 is at the student-by-course level. Treatment effects are estimated from a regression of the outcome on a 3-way interaction between treatment, non-male gender, and an indicator for family income under $100,000; and strata dummies (female and non-binary, with male the omitted third strata). Regressions also include course fixed effects. Students with unknown family income are excluded from this analysis. Outcomes are measured in Fall 2024. Robust standard errors clustered at the student level in parentheses. Control means in brackets.

Table 12: Treatment Effects on Exam and Course Performance, by Quantitative Test Score

	Exam score (out of 100)	Final course score (out of 100)
Above-median SAT/ACT math		
Men	-1.246	-1.645
	(2.234)	(1.430)
	[88.408]	[91.943]
Women/NB	-1.530	0.050
	(1.987)	(1.154)
	[89.614]	[91.893]
Below median		
Men	-4.920	-2.628
	(5.219)	(3.096)
	[83.648]	[86.642]
Women/NB	-5.691**	-2.686*
	(2.460)	(1.608)
	[84.158]	[88.884]
N	421	339

Notes: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Analysis in Column 1 is at the student-by-course-by-exam level; analysis in Column 2 is at the student-by-course level. Treatment effects are estimated from a regression of the outcome on a 3-way interaction between treatment, non-male gender, and an indicator for below-median test score; and strata dummies (female and non-binary, with male the omitted third strata). Regressions also include course fixed effects. Test score is measured as the percentile on the math section of the SAT or ACT, or the average of the two if a student took both. The median is calculated within the analysis sample. Outcomes are measured in Fall 2024. Robust standard errors clustered at the student level in parentheses. Control means in brackets.

Table 13: Treatment Effects on Exam and Course Performance, by Race/Ethnicity

	Exam score (out of 100)	Final course score (out of 100)
Non-URM		
Men	-0.561	0.539
	(1.820)	(1.212)
	[88.262]	[89.612]
Women/NB	-3.774**	-1.421
	(1.722)	(1.023)
	[85.395]	[89.746]
URM		
Men	3.036	-3.207
	(8.446)	(7.013)
	[73.793]	[84.167]
Women/NB	2.185	2.563
	(5.366)	(3.669)
	[74.389]	[81.868]
N	573	438

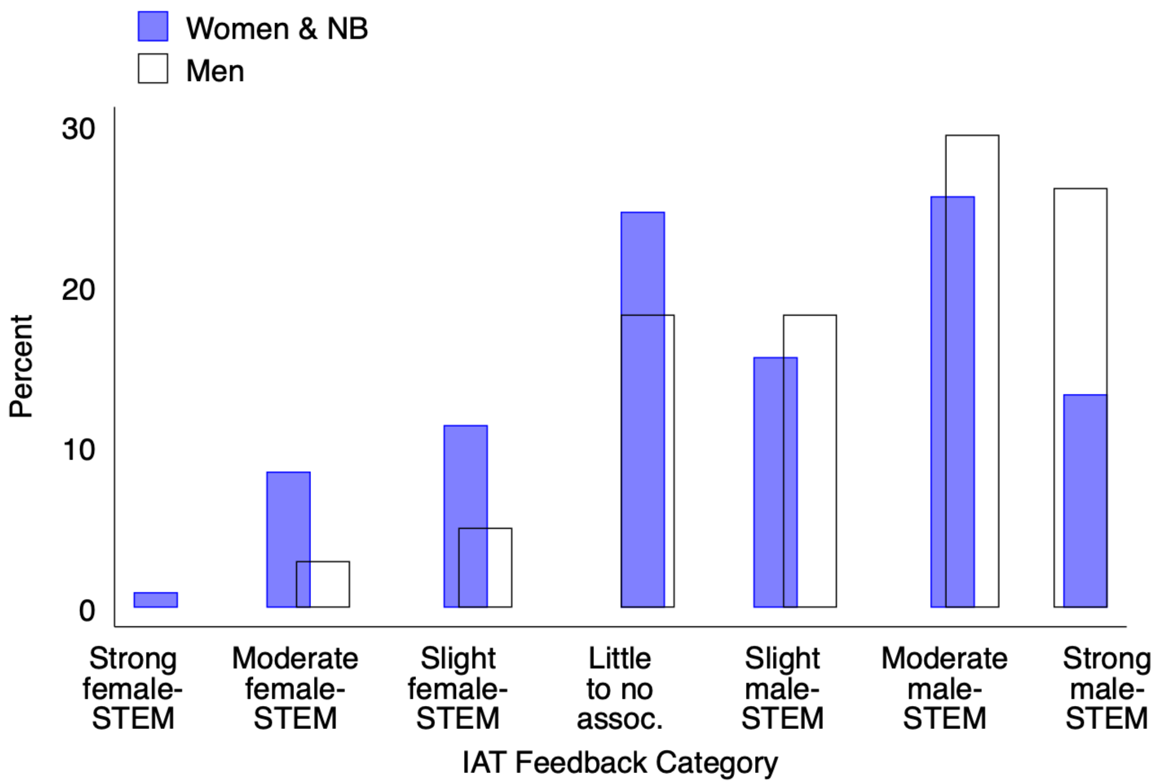
Notes: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. Analysis in Column 1 is at the student-by-course-by-exam level; analysis in Column 2 is at the student-by-course level. Treatment effects are estimated from a regression of the outcome on a 3-way interaction between treatment, non-male gender, and an indicator for underpresented minority; and strata dummies (female and non-binary, with male the omitted third strata). Regressions also include course fixed effects. URM includes Black, Hispanic, and Native students (including multi-racial/ethnic). Outcomes are measured in Fall 2024. Robust standard errors clustered at the student level in parentheses. Control means in brackets.

Table 14: Treatment Effects on STEM Course-taking and Major, by Intervention Feedback

	Any STEM courses (SP25)	# STEM courses	# STEM credits	Declared STEM major
Feedback: Male-STEM association				
Men	0.076**	0.126	0.423	-0.036
	(0.039)	(0.216)	(0.701)	(0.075)
	[0.887]	[2.577]	[8.923]	[0.443]
Women/NB	-0.043	-0.091	-0.416	-0.034
	(0.056)	(0.191)	(0.602)	(0.048)
	[0.710]	[1.758]	[5.710]	[0.210]
Feedback: Female-STEM association				
Men	0.057	0.057	1.386	0.284
	(0.166)	(0.620)	(1.901)	(0.194)
	[0.818]	[1.818]	[5.364]	[0.091]
Women/NB	-0.056	0.202	0.143	-0.037
	(0.064)	(0.289)	(0.891)	(0.091)
	[0.905]	[2.190]	[7.643]	[0.310]
Feedback: No gender-STEM association				
Men	0.058	0.533	3.417**	0.258*
	(0.116)	(0.483)	(1.650)	(0.146)
	[0.792]	[2.167]	[6.833]	[0.292]
Women/NB	-0.068	0.260	0.104	-0.018
	(0.063)	(0.252)	(0.826)	(0.081)
	[0.887]	[2.161]	[7.468]	[0.306]
N	760	760	760	760

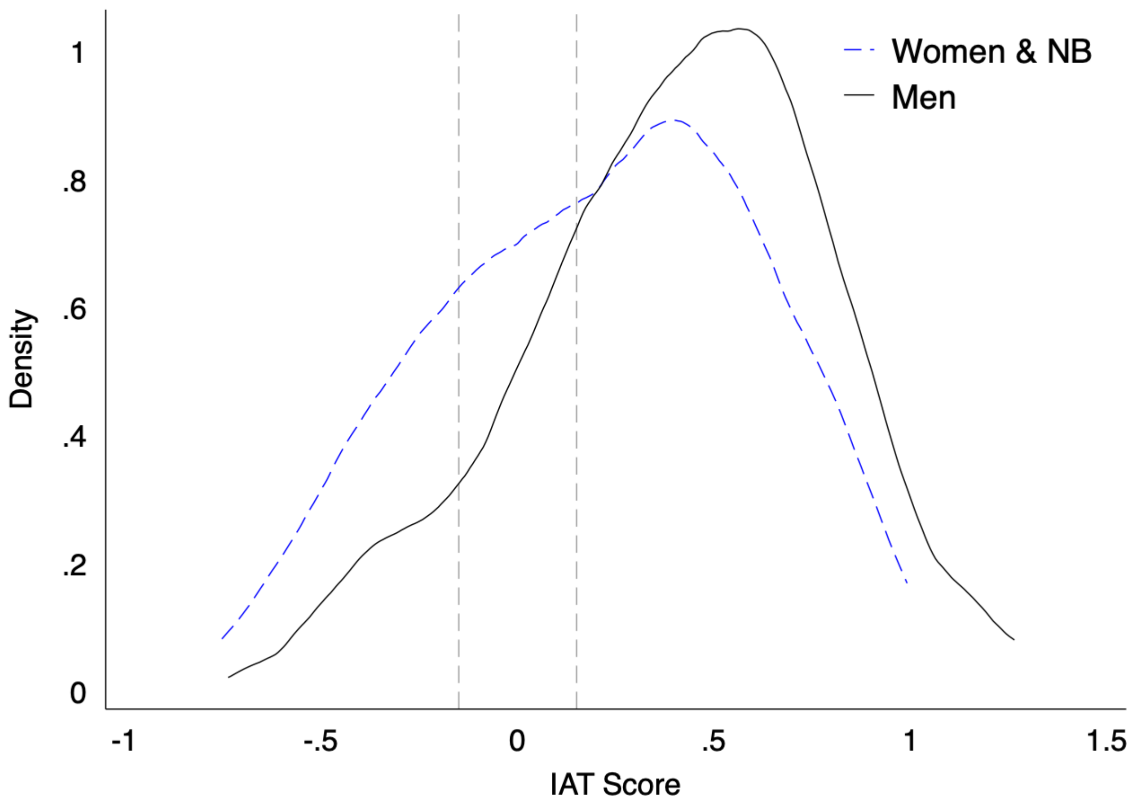
Notes: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Treatment effects are estimated from a regression of the outcome on a 3-way interaction between treatment, non-male gender, and initial message; and strata dummies (female and non-binary, with male the omitted third strata). Students without a valid IAT score (and therefore a treatment message) are excluded from this analysis. All outcomes are measured in Spring 2025 (the semester following the intervention). Robust standard errors in parentheses. Control means in brackets.

Figure 1: IAT Score Feedback Category, by Gender



Notes: Sample includes students who answered the pre-intervention student survey and completed the IAT (N=760; 519 women/NB students and 241 men). IAT is scored following the algorithm in Greenwald et al. (2003), and category thresholds follow (Greenwald et al., 2009). Treated students were told which category they fell into, while control students received no feedback.

Figure 2: IAT Score Raw Distribution, by Gender



Notes: Sample includes students who answered the pre-intervention student survey and completed the IAT (N=760; 519 women/NB students and 241 men). IAT is scored following the algorithm in Greenwald et al. (2003). Positive scores indicate an automatic association for male with STEM and female with humanities (stereotypical association) while negative scores indicate the non-stereotypical association. Scores with an absolute value less than 0.15 (region between gray lines) are considered to have little to no association either way (Greenwald et al., 2009).

Appendix A. Supplementary Exhibits

Table A1: Treatment Effects on STEM Course-taking and Major, Limited to Students with IAT Scores

	Any STEM courses (SP25)	# STEM courses	# STEM credits	Declared STEM major
Treatment effect on men	0.035	0.103	0.528	0.004
	(0.062)	(0.347)	(1.122)	(0.115)
Male control mean	[0.900]	[2.800]	[9.440]	[0.480]
Treatment effect on women/NB	-0.080	-0.036	-0.234	-0.079
	(0.056)	(0.214)	(0.702)	(0.062)
Female/NB control mean	[0.838]	[2.111]	[7.000]	[0.313]
N	287	287	287	287

Notes: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. This analysis is restricted to students with valid pre- and post-treatment IAT scores (the same sample in the final column of Table 5). Treatment effects are estimated from a regression of the outcome on a treatment indicator, an interaction between treatment and non-male gender, and strata dummies (female and non-binary, with male the omitted third strata). Robust standard errors in parentheses.

Table A2: Treatment Effects on IAT Task Response Time (Test for Manipulation)

	Average response time on IAT (milliseconds)
Treatment effect on men	-31.032
	(43.250)
Male control mean	[922.789]
Treatment effect on women/NB	27.310
	(25.641)
Female/NB control mean	[865.678]
N	287

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Treatment effects are estimated from a regression of the outcome on a treatment indicator, an interaction between treatment and non-male gender, strata dummies (female and non-binary, with male the omitted third strata), and the pre-treatment outcome. The outcome is the average response time, in milliseconds, across the 120 tasks in the four IAT blocks used for scoring. Robust standard errors in parentheses.

Table A3: Treatment Effects on STEM Course-taking and Major, by Parental Education

	Any STEM courses (SP25)	# STEM courses	# STEM credits	Declared STEM major
College-educated parent				
Men	0.081*	0.291	1.356**	0.072
	(0.042)	(0.204)	(0.677)	(0.065)
	[0.843]	[2.402]	[8.067]	[0.370]
Women/NB	-0.048	-0.007	-0.336	-0.060
	(0.039)	(0.142)	(0.456)	(0.041)
	[0.803]	[2.005]	[6.755]	[0.298]
First-gen student				
Men	0.043	0.427	0.902	-0.015
	(0.069)	(0.364)	(1.158)	(0.138)
	[0.917]	[2.333]	[8.458]	[0.375]
Women/NB	-0.028	0.298	0.704	0.023
	(0.080)	(0.299)	(0.879)	(0.069)
	[0.774]	[1.849]	[5.774]	[0.151]
N	865	865	865	865

Notes: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Treatment effects are estimated from a regression of the outcome on a 3-way interaction between treatment, non-male gender, and an indicator for first-generation status; and strata dummies (female and non-binary, with male the omitted third strata). Students with unknown parent education excluded from this analysis. Robust standard errors in parentheses; control means in brackets.

Table A4: Treatment Effects on STEM Course-taking and Major, by Class Year

	Any STEM courses (SP25)	# STEM courses	# STEM credits	Declared STEM major
First-year students				
Men	0.108**	0.384**	1.690**	0.063
	(0.042)	(0.193)	(0.655)	(0.063)
	[0.819]	[2.307]	[7.791]	[0.346]
Women/NB	-0.035	0.109	0.003	-0.027
	(0.039)	(0.143)	(0.449)	(0.037)
	[0.776]	[1.862]	[6.271]	[0.219]
Sophomores and above				
Men	-0.016	0.160	0.037	0.082
	(0.063)	(0.485)	(1.370)	(0.150)
	[0.963]	[2.630]	[8.963]	[0.444]
Women/NB	-0.129*	-0.274	-1.034	-0.100
	(0.071)	(0.279)	(0.904)	(0.093)
	[0.889]	[2.426]	[7.778]	[0.463]
N	876	876	876	876

Notes: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Treatment effects are estimated from a regression of the outcome on a 3-way interaction between treatment, non-male gender, and an indicator for first-year; and strata dummies (female and non-binary, with male the omitted third strata). Robust standard errors in parentheses; control means in brackets.

Table A5: Treatment Effects on Survey Outcomes, by Intervention Feedback

	Top choice major STEM	2nd choice major STEM	Prop. belief female STEM	Prop. belief female human.	IAT score (stdz.)
Feedback: Male-STEM association					
Men	-0.015	0.009	2.853**	-2.716*	-0.338
	(0.031)	(0.089)	(1.422)	(1.580)	(0.219)
	[0.776]	[0.667]	[42.408]	[59.837]	[0.557]
Women/NB	0.070	-0.038	3.099**	-2.300	0.037
	(0.053)	(0.072)	(1.511)	(1.744)	(0.177)
	[0.507]	[0.429]	[41.897]	[65.147]	[0.077]
Feedback: Female-STEM association					
Men	-0.519*	0.313	9.669***	-6.333***	0.604
	(0.293)	(0.376)	(3.710)	(2.105)	(0.419)
	[0.600]	[0.400]	[40.000]	[58.000]	[-0.644]
Women/NB	-0.104	0.096	2.055	-6.241***	-0.106
	(0.077)	(0.114)	(2.200)	(2.162)	(0.316)
	[0.842]	[0.556]	[46.684]	[63.158]	[-0.612]
Feedback: No gender-STEM association					
Men	-0.031	-0.161	2.066	-4.134	-0.530
	(0.071)	(0.197)	(2.713)	(3.159)	(0.459)
	[0.643]	[0.769]	[37.286]	[61.643]	[0.514]
Women/NB	-0.076	-0.090	-1.203	-2.917	-0.403*
	(0.072)	(0.116)	(2.160)	(2.203)	(0.228)
	[0.639]	[0.743]	[44.944]	[63.750]	[-0.044]
N	389	343	384	388	287

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Treatment effects are estimated from a regression of the outcome on a 3-way interaction between treatment, non-male gender, and initial message; pre-treatment measure of the outcome; and strata dummies (female and non-binary, with male the omitted third strata). Students without a valid IAT score (and therefore a treatment message) are excluded from this analysis. Robust standard errors in parentheses; control means in brackets.

Table A6: Treatment Effects on STEM Course-taking and Major, by Explicit and Implicit Beliefs

	Any STEM courses (SP25)	# STEM courses	# STEM credits	Declared STEM major
Men				
E=male, I=male	0.032	0.006	-0.093	-0.143*
(N=143)	(0.040)	(0.244)	(0.793)	(0.083)
	[0.922]	[2.675]	[9.442]	[0.506]
E=male, I=none	0.040	0.367	2.964*	0.217
(N=41)	(0.120)	(0.515)	(1.737)	(0.155)
	[0.810]	[2.333]	[7.286]	[0.333]
E=male, I=female	0.083	0.500	2.292	0.375
(N=14)	(0.233)	(0.820)	(2.557)	(0.254)
	[0.750]	[1.500]	[4.875]	[0.125]
E=female, I=male	0.211**	0.484	2.044	0.442***
(N=34)	(0.096)	(0.451)	(1.389)	(0.156)
	[0.789]	[2.316]	[7.289]	[0.158]
E=female, I=none	0.000	0.000	0.000	0.000
(N=3)	(0.000)	(0.000)	(0.000)	(0.000)
	[0.667]	[1.000]	[3.667]	[0.000]
E=female, I=female	0.000	-1.167	-1.167	0.000
(N=5)	(0.000)	(0.838)	(2.880)	(0.000)
	[1.000]	[2.667]	[6.667]	[0.000]
Women/NB				
E=male, I=male	-0.061	0.003	-0.210	-0.044
(N=229)	(0.062)	(0.209)	(0.663)	(0.055)
	[0.720]	[1.710]	[5.640]	[0.230]
E=male, I=none	-0.096	0.075	-0.327	-0.026
(N=101)	(0.071)	(0.274)	(0.925)	(0.093)
	[0.900]	[2.200]	[7.660]	[0.320]
E=male, I=female	-0.137*	-0.047	-0.629	-0.100
(N=80)	(0.072)	(0.334)	(1.043)	(0.108)
	[0.941]	[2.265]	[7.912]	[0.382]
E=female, I=male	0.057	-0.441	-1.138	0.013
(N=53)	(0.130)	(0.451)	(1.411)	(0.095)
	[0.667]	[1.958]	[6.000]	[0.125]
E=female, I=none	0.024	1.000	1.905	0.036
(N=26)	(0.148)	(0.637)	(1.951)	(0.181)
	[0.833]	[2.000]	[6.667]	[0.250]
E=female, I=female	0.200	0.925	2.450	0.250**
(N=28)	(0.167)	(0.620)	(1.852)	(0.100)
	[0.750]	[1.875]	[6.500]	[0.000]

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Each treatment effect is estimated from a separate regression of the outcome on a treatment indicator, for the subgroup. "E" refers to explicit beliefs; "E=male" means a student believes 50 percent or more of STEM degrees go to men. "I" refers to implicit stereotypes; "I=male" means a student implicitly associates STEM with male, as measured by the IAT. Robust standard errors in parentheses; control means in brackets.

Table A7: Treatment Effects on STEM Course-taking and Major, by Explicit and Implicit Beliefs, Using 40 Percent Cutoff for Explicit Beliefs

	Any STEM courses (SP25)	# STEM courses	# STEM credits	Declared STEM major
Men				
E=male, I=male	0.014	0.056	-1.031	-0.382***
(N=62)	(0.055)	(0.384)	(1.167)	(0.119)
	[0.946]	[2.784]	[10.351]	[0.622]
E=male, I=none	0.182	0.232	2.061	0.303
(N=20)	(0.123)	(0.657)	(2.278)	(0.225)
	[0.818]	[2.545]	[8.273]	[0.364]
E=male, I=female	0.000	2.000	4.000	0.500
(N=3)	(0.000)	(1.225)	(2.449)	(0.612)
	[1.000]	[3.000]	[10.000]	[0.500]
E=female, I=male	0.100*	0.151	1.179	0.160*
(N=115)	(0.051)	(0.266)	(0.858)	(0.091)
	[0.864]	[2.492]	[8.178]	[0.322]
E=female, I=none	-0.042	0.790	4.566*	0.224
(N=24)	(0.186)	(0.724)	(2.441)	(0.199)
	[0.769]	[1.846]	[5.615]	[0.231]
E=female, I=female	0.079	-0.127	1.381	0.286
(N=16)	(0.205)	(0.509)	(1.841)	(0.183)
	[0.778]	[1.556]	[4.333]	[0.000]
Women/NB				
E=male, I=male	-0.068	0.117	-0.091	-0.019
(N=114)	(0.097)	(0.319)	(1.029)	(0.075)
	[0.641]	[1.590]	[5.231]	[0.179]
E=male, I=none	-0.275**	-0.408	-1.608	-0.190
(N=35)	(0.129)	(0.492)	(1.811)	(0.159)
	[0.941]	[2.353]	[7.941]	[0.412]
E=male, I=female	-0.313*	-0.137	-1.253	0.099
(N=27)	(0.157)	(0.666)	(1.998)	(0.188)
	[0.929]	[2.214]	[7.714]	[0.286]
E=female, I=male	0.018	-0.185	-0.435	-0.031
(N=168)	(0.067)	(0.229)	(0.736)	(0.063)
	[0.741]	[1.835]	[5.929]	[0.224]
E=female, I=none	0.006	0.528*	0.796	0.052
(N=92)	(0.071)	(0.294)	(0.922)	(0.096)
	[0.867]	[2.089]	[7.289]	[0.267]
E=female, I=female	0.013	0.293	0.506	-0.076
(N=81)	(0.072)	(0.332)	(1.034)	(0.108)
	[0.893]	[2.179]	[7.607]	[0.321]

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Each treatment effect is estimated from a separate regression of the outcome on a treatment indicator, for the subgroup. "E" refers to explicit beliefs; "E=male" means a student believes 40 percent or more of STEM degrees go to men. "I" refers to implicit stereotypes; "I=male" means a student implicitly associates STEM with male, as measured by the IAT. Robust standard errors in parentheses; control means in brackets.

Appendix B. Survey Instruments

B.1. Pre-Intervention Survey (September 2024)

[*gender*]

Please select your gender identity.

- ○ Female
- ○ Male
- ○ Non-binary
- ○ Other: _____
- ○ Prefer not to say

First, we would like to ask you some questions about your academic plans at the University of the Midwest.

[*expected_major_1*]

At UM, there are dozens of academic majors to choose from. What major do you think you're **most likely** to graduate with a degree in? If you plan to double major, please select what you consider to be your primary major.

Science, Technology, Engineering, and Math (STEM)

- ○ Engineering
- ○ Biology
- ○ Natural science other than biology (astronomy, chemistry, earth science, geology, physics, etc.)
- ○ Computer science
- ○ Math
- ○ Statistics
- ○ Neuroscience

Humanities

- ○ Arts (visual, performing, etc.)
- ○ Languages (Spanish, French, Chinese, etc.)
- ○ Other humanities (English, philosophy, history, etc.)

Social Sciences

- ○ Economics
- ○ Psychology
- ○ Social science other than econ or psych (political science, sociology, etc.)

Other

- ○ Business

- Health-related (e.g., kinesiology/movement science, pharmacy, public health, etc.)
- Public policy
- Other (please fill in)

[*expected_major_2*]

What major do you think you're **second most likely** to graduate with a degree in? If you plan to double major, this would be your second major.

Science, Technology, Engineering, and Math (STEM)

- Engineering
- Biology
- Natural science other than biology (astronomy, chemistry, earth science, geology, physics, etc.)
- Computer science
- Math
- Statistics
- Neuroscience

Humanities

- Arts (visual, performing, etc.)
- Languages (Spanish, French, Chinese, etc.)
- Other humanities (English, philosophy, history, etc.)

Social Sciences

- Economics
- Psychology
- Social science other than econ or psych (political science, sociology, etc.)

Other

- Business
- Health-related (e.g., kinesiology/movement science, pharmacy, public health, etc.)
- Public policy
- Other (please fill in)

[*expected_salary_1*]

Assume you graduate with a bachelor's degree in **[*expected_major_1*]** (and no double major). How much money do you predict you would make per year, at age 40, with that major? (If you expect to make more than $300,000, please select 300 below.)

$ 0 K $ 50 K $ 100 K $ 150 K $ 200 K $ 250 K $300 K

Expected salary (thousands of $)

[*expected_salary_2*]

Assume you graduate with a bachelor's degree in **[*expected_major_2*]** (and no double major). How much money do you predict you would make per year, at age 40, with that major? (If you expect to make more than $300,000, please select 300 below.)

$ 0 K $ 50 K $ 100 K $ 150 K $ 200 K $ 250 K $300 K

Expected salary (thousands of $)

[*major_factors*]

How important are/were each of the following in choosing your major?

Not at all important 1	Slightly important 2	Moderately important 3	Very important 4	Extremely important 5

Feeling like I'm good at the subject

Being engaged with the coursework (while in school)

Making/having friends or study partners in the major

Expected salary (after graduation)

Work flexibility (after graduation)

Having a positive impact on society (after graduation)

Work culture/peers (after graduation)

Next, we have a few questions about students and majors at UM.

[*pct_stem_women*]

Think about all of the undergraduate students who graduated from UM last year with a Bachelor's degree in a **science, technology, engineering, or math (STEM) subject**. What proportion of those students would you estimate are women?

0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%

Percent of UM STEM degrees going to women

[*pct_humanities_women*]

Think about all of the undergraduate students who graduated from UM last year with a Bachelor's degree in a **humanities** subject (includes English, languages, arts, history, philosophy, etc.). What proportion of those students would you estimate are women?

0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%

Percent of UM humanities degrees going to women

[*stem_hs_gpa*]

Again, think about all of the undergraduate students who graduated from UM last year with a Bachelor's degree in a **science, technology, engineering, or math (STEM) subject**. What do you think was the **average high school GPA** of these STEM majors?

E/F	D	C	B	A
0	1	2	3	4

STEM majors' high school GPA

[*hum_hs_gpa*]

Again, think about all of the undergraduate students who graduated from UM last year with a Bachelor's degree in a **humanities** subject (includes English, languages, arts, history, philosophy, etc.). What do you think was the **average high school GPA** of these humanities majors?

E/F	D	C	B	A
0	1	2	3	4

Humanities majors' high school GPA

Now we'd like to ask you a couple of questions about your high school experience.

[*fav_teacher_hum*]

Think back to all of the **English and social studies** courses you took in high school. Who was your favorite high school teacher in those subjects?

	Title	Last name (fill in)
Favorite English/social studies teacher:		

[*fav_teacher_stem*]

Think back to all of the **math and science courses** you took in high school. Who was your favorite high school teacher in those subjects?

	Title	Last name (fill in)
Favorite math/science teacher:		

Thank you very much for answering the previous questions. As the second part of the study, we will now direct you to a link to take an implicit association test, or IAT. Completing the IAT should take about 5 minutes.

Please click the link below to take the Implicit Association Test. After you complete the IAT, you will be automatically entered into a lottery to win a $50 Amazon gift card.

Click here to take the IAT and complete the study.

B.2. Post-Intervention Survey (December 2024)

First, we would like to ask you some questions about your academic plans at the University of the Midwest.

[*expected_major_1*]

At UM, there are dozens of academic majors to choose from. What major do you think you're **most likely** to graduate with a degree in? If you plan to double major, please select what you consider to be your primary major.

Science, Technology, Engineering, and Math (STEM)

- ○ Engineering
- ○ Biology
- ○ Natural science other than biology (astronomy, chemistry, earth science, geology, physics, etc.)
- ○ Computer science
- ○ Math
- ○ Statistics
- ○ Neuroscience

Humanities

- ○ Arts (visual, performing, etc.)
- ○ Languages (Spanish, French, Chinese, etc.)
- ○ Other humanities (English, philosophy, history, etc.)

Social Sciences

- ○ Economics
- ○ Psychology
- ○ Social science other than econ or psych (political science, sociology, etc.)

Other

- ○ Business
- ○ Health-related (e.g., kinesiology/movement science, pharmacy, public health, etc.)
- ○ Public policy
- ○ Other (please fill in)

[*expected_major_2*]

What major do you think you're **second most likely** to graduate with a degree in? If you plan to double major, this would be your second major.

Science, Technology, Engineering, and Math (STEM)

- ○ Engineering
- ○ Biology
- ○ Natural science other than biology (astronomy, chemistry, earth science, geology, physics, etc.)
- ○ Computer science
- ○ Math
- ○ Statistics
- ○ Neuroscience

Humanities

- ○ Arts (visual, performing, etc.)
- ○ Languages (Spanish, French, Chinese, etc.)
- ○ Other humanities (English, philosophy, history, etc.)

Social Sciences

- ○ Economics
- ○ Psychology
- ○ Social science other than econ or psych (political science, sociology, etc.)

Other

- ○ Business
- ○ Health-related (e.g., kinesiology/movement science, pharmacy, public health, etc.)
- ○ Public policy
- ○ Other (please fill in)

Next, we have a few questions about students and majors at UM.

[*pct_stem_women*]

Think about all of the undergraduate students who graduated from UM last year with a Bachelor's degree in a **science, technology, engineering, or math (STEM) subject**. What proportion of those students would you estimate are women?

0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%

Percent of UM STEM degrees going to women

[*pct_humanities_women*]

Think about all of the undergraduate students who graduated from UM last year with a Bachelor's degree in a **humanities** subject (includes English, languages, arts, history, philosophy, etc.). What proportion of those students would you estimate are women?

0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%

Percent of UM humanities degrees going to women

Thank you very much for answering the previous questions. As the second part of the study, we will now direct you to a link to take an implicit association test, or IAT, just like the one you took earlier this semester. Completing the IAT should take about 5 minutes.

Please click the link below to take the Implicit Association Test. After you complete the IAT, you will be automatically entered into a lottery to win a $50 Amazon gift card.

Click here to take the IAT and complete the study.

Appendix C. IAT Details

The IAT consists of seven blocks, with between 20 and 40 tasks per block, summarized in Table C1. Each task requires a participant to sort a word to the left or right of a computer, tablet, or phone screen, using keystrokes or touch. The words fall into four categories: male, female, STEM, and humanities. Figure C1 lists all possible words. We use the standard gender-science IAT, with the slight modification of renaming the "science" category "STEM," and renaming the "liberal arts" category "humanities."

The correct sorting depends on the block. There are three practice rounds that familiarize participants with the procedure (e.g., sorting STEM words to one side and humanities to another; and the same for male and female). In the four rounds used for scoring, participants must either sort male and STEM words to one side and female and humanities to the other (stereotypical pairing), or sort male and humanities to one side and female and STEM to the other (non-stereotypical). Within a block, words are presented randomly. For example, in block 3, a participant might see the first six words: Engineering, Math, Uncle, English, Woman, Son; another might see Mother, Chemistry, Literature, Wife, Father, Daughter. Figure C2 shows screenshots of sample tasks.

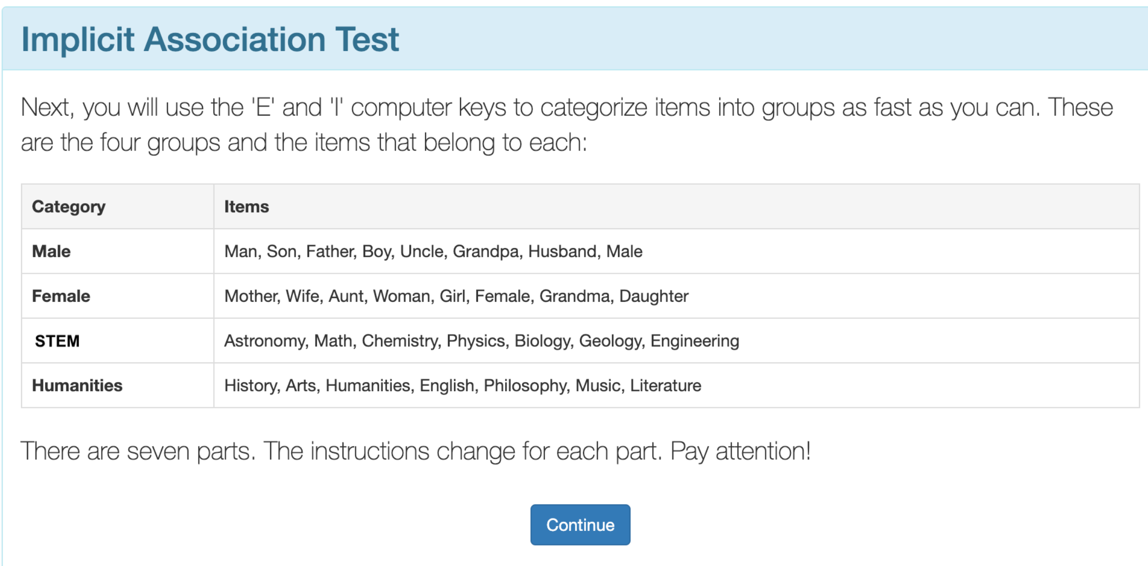
The IAT used in this study was "counterbalanced," meaning the order in which participants are asked to do the stereotype-conforming versus non-conforming tasks is randomly assigned. In other words, half of our participants saw the blocks in the order listed in Table C1, and the rest saw them in the order of 1, 2, 6, 7, 5, 3, 4.

Table C1: Summary of IAT Blocks

Block	Left Categories	Right Categories	Number of Tasks
1	STEM	Humanities	20
2	Male	Female	20
3*	Male STEM	Female Humanities	20
4*	Male STEM	Female Humanities	40
5	Humanities	STEM	28
6*	Male Humanities	Female STEM	20
7*	Male Humanities	Female STEM	40

Notes: Participants were randomly (and orthogonal to treatment assignment) presented with an IAT using the order above, or in the order of 1, 2, 6, 7, 5, 3, 4. Blocks 3, 4, 6, and 7 (*) are used in scoring; the remaining blocks are practice rounds.

Figure C1: Categories and Words in Gender-Science IAT



Implicit Association Test

Next, you will use the 'E' and 'I' computer keys to categorize items into groups as fast as you can. These are the four groups and the items that belong to each:

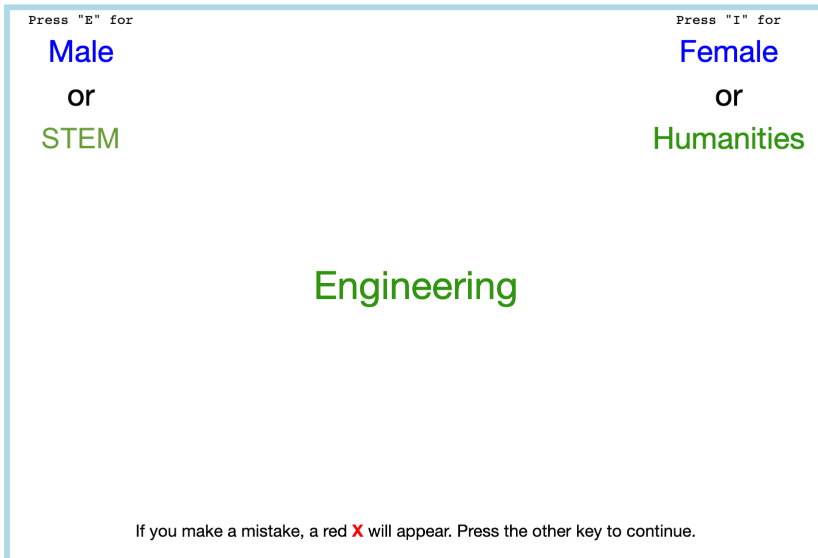
Category	Items
Male	Man, Son, Father, Boy, Uncle, Grandpa, Husband, Male
Female	Mother, Wife, Aunt, Woman, Girl, Female, Grandma, Daughter
STEM	Astronomy, Math, Chemistry, Physics, Biology, Geology, Engineering
Humanities	History, Arts, Humanities, English, Philosophy, Music, Literature

There are seven parts. The instructions change for each part. Pay attention!

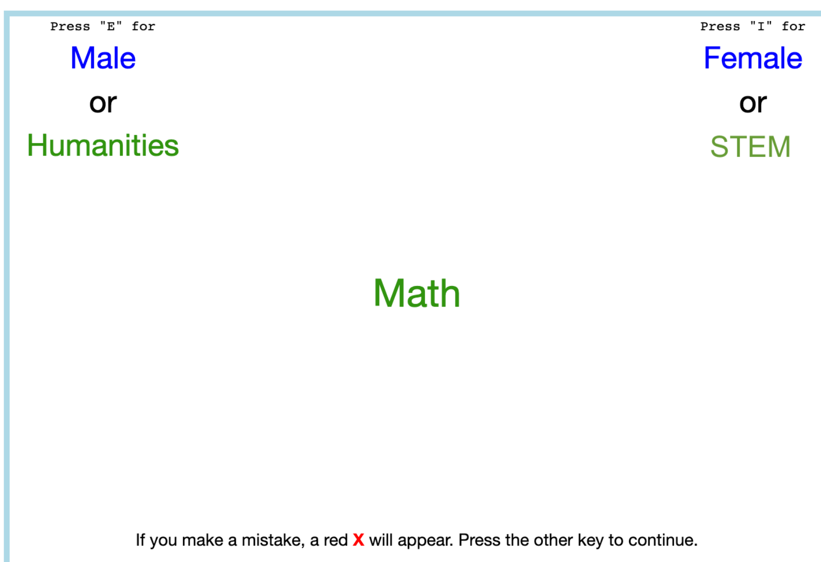
Continue

Notes: This is a screenshot from the keyboard device version of the IAT. The touchscreen version specifies the participant will touch the left or right side of the screen.

Figure C2: Sample IAT Tasks



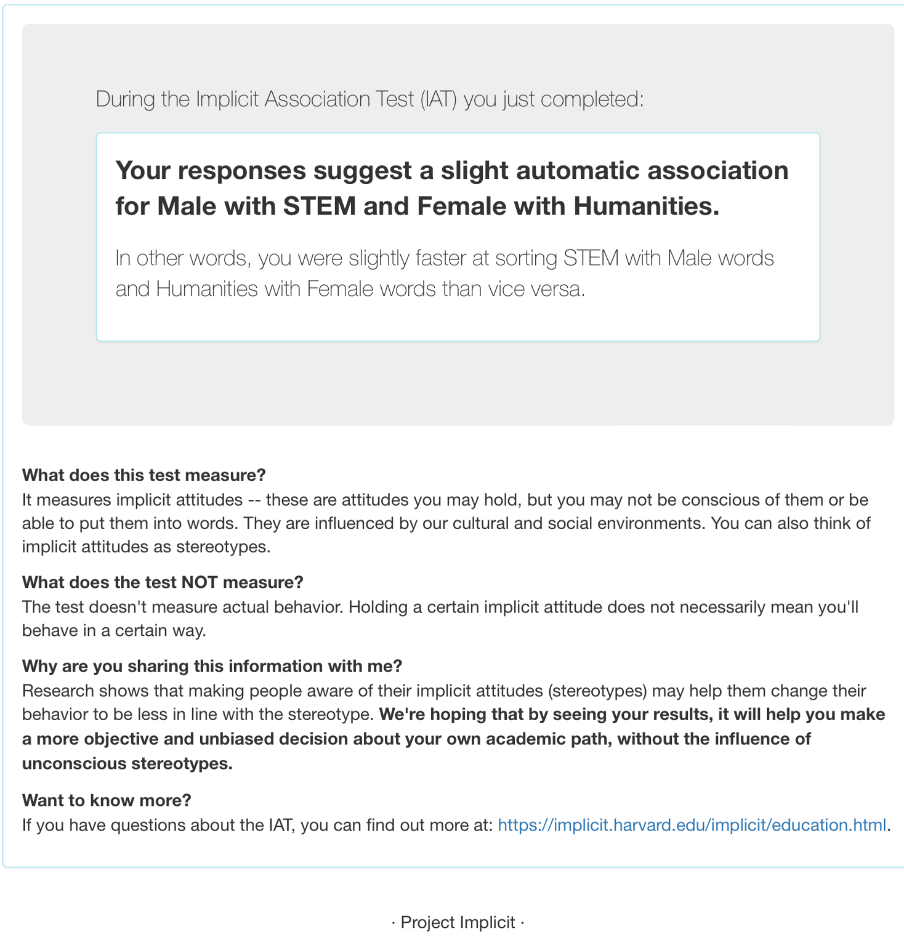
(a) Male-STEM/female-humanities
(stereotypical)



(b) Male-humanities/female-STEM
(non-stereotypical)

Appendix D. Treatment Messages

Figure D1: Sample Treatment Message for Participant with Slight Male-STEM Association



During the Implicit Association Test (IAT) you just completed:

Your responses suggest a slight automatic association for Male with STEM and Female with Humanities.

In other words, you were slightly faster at sorting STEM with Male words and Humanities with Female words than vice versa.

What does this test measure?
It measures implicit attitudes -- these are attitudes you may hold, but you may not be conscious of them or be able to put them into words. They are influenced by our cultural and social environments. You can also think of implicit attitudes as stereotypes.

What does the test NOT measure?
The test doesn't measure actual behavior. Holding a certain implicit attitude does not necessarily mean you'll behave in a certain way.

Why are you sharing this information with me?
Research shows that making people aware of their implicit attitudes (stereotypes) may help them change their behavior to be less in line with the stereotype. **We're hoping that by seeing your results, it will help you make a more objective and unbiased decision about your own academic path, without the influence of unconscious stereotypes.**

Want to know more?
If you have questions about the IAT, you can find out more at: https://implicit.harvard.edu/implicit/education.html.

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Figure D2: Sample Treatment Message for Participant with Strong Female-STEM Association

During the Implicit Association Test (IAT) you just completed:

Your responses suggest a strong automatic association for Female with STEM and Male with Humanities.

In other words, you were much faster at sorting STEM with Female words and Humanities with Male words than vice versa.

What does this test measure?
It measures implicit attitudes -- these are attitudes you may hold, but you may not be conscious of them or be able to put them into words. They are influenced by our cultural and social environments. You can also think of implicit attitudes as stereotypes.

What does the test NOT measure?
The test doesn't measure actual behavior. Holding a certain implicit attitude does not necessarily mean you'll behave in a certain way.

Why are you sharing this information with me?
Research shows that making people aware of their implicit attitudes (stereotypes) may help them change their behavior to be less in line with the stereotype. **We're hoping that by seeing your results, it will help you make a more objective and unbiased decision about your own academic path, without the influence of unconscious stereotypes.**

Want to know more?
If you have questions about the IAT, you can find out more at: https://implicit.harvard.edu/implicit/education.html.

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