Do Performance Avoidance Goals Moderate the Effect of Different Types of Stereotype Threat
on Women's Math Performance?

Katherine M. Finnigan¹, Katherine S. Corker²

¹University of California, Davis, ²Kenyon College

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Correspondence concerning this article should be addressed to Katherine S. Corker, Department of Psychology, Kenyon College, 203 N. College Rd., Gambier, OH 43022. Email: corkerk@kenyon.edu.

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Abstract

Stereotype threat is considered to be a robust effect that explains persistent gender gaps in math performance and scientific career trajectories. Some evidence suggests stereotype threat effects are buffered by adoption of performance avoidance goals (Chalabaev et al., 2012). With 590 American female participants, we closely replicated Chalabaev et al. (2012). Results showed no significant main or interaction effects for stereotype threat or performance avoidance goals, despite multiple controls. We conclude that effects of stereotype threat might be smaller than typically reported and find limited evidence for moderation by avoidance achievement goals. Accordingly, stereotype threat might not be a major part of the explanation for the gender gap in math performance, consistent with recent meta-analyses (Flore & Wicherts, 2015).

Keywords: Stereotype threat; academic achievement; achievement goals; gender stereotypes;

math achievement

Highlights:

- This paper is a close replication of Chalabaev, Major, Sarrazin, & Cury (2012)
- We tested for an interaction between stereotype threat and achievement goals
- We found no significant main or interaction effects for threat or goals
- No significant effects emerged despite multiple controls
- We suggest that the effect of stereotype threat may be weaker than commonly thought

Do Performance Avoidance Goals Moderate the Effect of Different Types of Stereotype Threat on Women's Math Performance?

Despite research suggesting girls receive higher marks than boys across all subjects, including math and science courses, girls in the United States score lower than boys on the math section of the SAT (The College Board, 2013; $d = -0.27$), and make up only 25% of the STEM (science, technology, engineering, and mathematics) workforce when women make up 47% of the overall workforce (National Math and Science Initiative, 2013). Given the importance of standardized tests for college admissions, the need for research to accurately identify the forces behind women's poorer performance on tests of math ability is imperative for optimal interventions and policy changes. The present research aimed to replicate the effect of stereotype threat on math performance and to determine how different types of stereotype threat impact performance. Few direct replications of stereotype threat have been published, and we aim to test this effect in a large online sample of American women. Further, we tested how threat interacts with performance avoidance goals, which are defined as aiming at avoiding poor performance relative to one's peers (Elliot & McGregor, 2001).

1.1 Different types of stereotype threat

One of the most prominent psychological theories used to explain the math-achievement gap is stereotype threat, which occurs when individuals are fearful of confirming negative stereotypes associated with their group. Steele and Aronson (1995) posit that “in situations where the stereotype is applicable, one is at risk of confirming it as a self-characterization, both to one's self and to others who know the stereotype” (p. 808). This theory was applied to the women in mathematics stereotype by Spencer, Steele, and Quinn (1999) — a landmark paper that illustrated the negative effect of framing a test as diagnostic of math ability or gender differences

on female math performance. Many studies have used cues stemming from Spencer et al., ranging from test framings to threatening test administrators (Shapiro & Neuberg, 2007). Recent research has attempted to make sense of these different types of stereotype threat and how they distinctly impact performance.

Shapiro and Neuberg's (2007) multi-threat framework classifies threats based on the threat's source and target. The three sources of stereotype threat are self, outgroup (e.g., men), and ingroup (e.g., other women in mathematics). The two targets of threat are the self and the group (e.g., an individual woman is the self, the female gender as a whole is the group). The authors theorize that these threats have different effects on individuals; for example, group-as-target threats are believed to lead to more negative comparisons between the self and ingroup and outgroup members than self-as-target threats do. The current study focuses on two "self-as-source" threats: *group-concept threat* and *self-concept threat*. Group-concept threat targets the stereotyped group to which one belongs and differentiates the stereotyped group from the majority (e.g., men in mathematics). Group-concept threats thus confirm, to a woman in mathematics, that her *gender as a whole* is bad at math. Self-concept threat is the fear that one's performance will confirm that *oneself* is bad at math. Unlike group-concept threat, self-concept threat targets one's inherent attributes or skills, and self-concept threat does not require identification with the group (Shapiro & Neuberg, 2007). Using two threat manipulations, we aimed to experimentally test if self-concept threat or group-concept threat differentially affect math test performance and if these threats interact with variables believed to moderate the effect of stereotype threat (e.g., gender identity and math identity).

1.2 Threat and performance avoidance goals

In the last decade, stereotype threat research has shifted in focus from investigating the existence of stereotypes to examining the mechanisms that influence test performance for women (Shapiro & Williams, 2012). Performance avoidance goals have been identified as a potential consequence of stereotype threat for women in mathematics because individuals endorse those goals to avoid performing poorly in comparison to peers (Elliot & McGregor, 2001). For example, if a student aims to prevent scoring low on the SAT in comparison to her friends and other students she knows, she adopts a performance avoidance goal orientation. Performance avoidance goals and stereotype threat are associated with anxiety, fear of failure, and negative evaluations of self-competence, and thus they typically impair performance (Smith, Sansone, & White, 2007).

However, individuals who adopt performance-avoidance goals are in a state similar to those completing tasks that are inherently threatening, and theory suggests that matching goal orientation to task characteristics boosts performance (Cesario, Higgins, & Scholer, 2008). Stereotype threat (particularly group-concept threat) emphasizes social comparisons, a feature that is an integral component of performance-avoidance goals. Grimm, Markman, Maddox, and Baldwin (2009) posit that an avoidance goal orientation matches a stereotype threat situation better than an approach goal orientation does; this fit may then lead stereotyped individuals to use cognitive strategies that help them avoid negative outcomes and perform as well as non-threatened individuals.

This matching effect has been tested and found in studies on stereotype threat for women in math. Chalabaev, Major, Sarrazin, and Cury (2012) operationalized stereotype threat through a “math ability” cue (self-concept threat) in one study and a “gender differences” cue (group-concept threat) in a second study, in accordance with Spencer et al.’s (1999) manipulations. Both

of Chalabaev et al.'s studies demonstrated that inducing a performance-avoidance goal produces better performance under stereotype threat on a math test when compared to no goal, an effect subsequently detected by others (Deemer, Smith, Carroll, & Carpenter, 2014).

1.3 The present study

Given the theoretical links between stereotype threat and performance-avoidance goals and the evidence supporting their interaction, we sought (1) to test this interaction in a large-scale, pre-registered replication, using Chalabaev et al.'s (2012) basic design, and (2) to extend their design to directly compare two types of threat from Shapiro and Neuberg's (2007) framework. Additionally, we tested for differences in magnitude of effect between self-concept and group-concept threat with various moderators (detailed below). We predicted that we would find a stereotype threat by performance avoidance goal interaction, such that women under threat would perform better on a math test with a performance avoidance goal compared to no goal. We also predicted that the effect of group-concept threat would be stronger when compared to self-concept threat. We tested these hypotheses with an all-female sample, because the performance of males is not inhibited by stereotype threat in the domain of mathematics (Walton & Cohen, 2003).

Replications of stereotype threat studies are relatively uncommon, and we aimed to test this effect in a larger sample than the vast majority of research in this area (Stoet & Geary, 2012). Policymakers and social psychologists point to stereotype threat as a major force behind the gender gap in STEM, although there are few tests of stereotype threat in this domain on samples of non-undergraduates (Flore & Wicherts, 2015). By conducting highly-powered test of stereotype threat in a diverse sample, this study will provide insight into the generalizability of

stereotype threat, and it will test the extent to which threat can impact performance in an online setting.

Method

2.1 Pilot Study & Design

We pre-registered our design and analysis plan (see <https://osf.io/kms6g>). In order to measure math performance under differing conditions of stereotype threat, we used 10 released questions from the GRE quantitative reasoning section, also used in Chalabaev et al. (2012). We ran a pilot study testing math ability with three tests of different degrees of difficulty (i.e., sixth grade, tenth grade, and the GRE) to ensure that these questions were appropriately difficult for the intended audience of female Mechanical Turk workers. The GRE was best suited to enable the detection of stereotype threat, as per Spencer et al. (1999), because the other two tests were not difficult enough; see the online supplemental materials, also available at <https://osf.io/jze8c/>, for more detailed results of the pilot study.

In order to determine the appropriate sample size for hypothesis tests, we conducted a sensitivity analysis using R Statistical Software (Version 3.1.1), specifically the *pwr* package (Champley, 2012). The analyses revealed that with 600 participants (100 in each condition) and 80% power, assuming $\alpha = .05$, the study could reliably detect an effect of $d = 0.40$. With the same number of participants and 90% power assuming $\alpha = .05$, the study could detect an effect of $d = 0.46$.

We therefore aimed to collect 600 participants. Hypotheses were tested in a 3 (Type of Threat: Self-Concept Threat, Group-Concept Threat, No Threat) $\times$ 2 (Goal: Performance Avoidance vs. No Goal) between-subjects design.

2.2 Materials

2.2.1 Stereotype Threat and Achievement Goal Manipulations. Participants received one of six prompts, in the form of audio instructions. In the neutral (no threat), no goal condition, participants were told, “You are going to perform a problem solving test.” In the math ability (self-concept threat), no goal condition, participants were told, “You are going to perform a math test.” In the gender differences (group-concept threat), no goal condition, participants were told, “Previous research has sometimes shown gender differences in math ability...the test you are about to take has been shown to produce gender differences.” In all three performance avoidance goal conditions, participants were additionally told that the test “is designed to help us identify people who are exceptionally weak in their mathematical reasoning abilities.” See <https://osf.io/ac259/> for full text of the manipulations.

2.2.2 Math Performance. Each of the 10 questions was multiple-choice with five answer choices per question. This set of questions was shown to be a fairly reliable measure of math performance within this sample ($M = 4.32$, $SD = 2.22$, $\alpha = .63$).

2.2.3 Math and Gender Identity. The Math Identification Questionnaire (MIQ; Brown & Josephs, 2000) is a measure of domain identification with mathematics; individuals who are highly math-identified are thought to consider their mathematics abilities and skills to be important parts of their identity, and they highly value mathematics (Brown & Josephs, 2000). The questionnaire contained four items (e.g., “My math abilities are very important to me”) rated on a Likert scale of 1 (*strongly disagree*) to 7 (*strongly agree*). For this sample, the average of the four questions produced a reliable index of math identification ($\alpha = .75$), with an average score of $M = 4.18$ ($SD = 1.34$). We computed a Pearson’s r correlation between the MIQ score and the number of GRE questions correctly answered and found a moderate, positive correlation between MIQ scores and math test scores ($r = .31$).

Schmader (2002) modified four items from the Collective Self-Esteem Scale (Luhtanen & Crocker, 1992) in order to assess the “perceived importance of gender identity to self-definition” (Schmader, 2002, p. 196). These same four items (e.g., “Being a woman is an important reflection of who I am”) were rated by our participants on a Likert scale of 1 (*strongly disagree*) to 7 (*strongly agree*). As in Schmader (2002), this set of questions was a reliable measure of gender identity ($\alpha = .84$). We averaged the four items together ($M = 5.10$, $SD = 1.34$). The correlation with math test scores was not significantly different from zero ($r = -.02$).

To test the hypothesis, it is required that participants be identified with the domain in question (math) and with their gender (female; Steele, 1997). We compared the scale means in the current sample to values obtained in other published studies. When necessary, we transformed these published values to a seven-point scale by dividing means and standard deviations by the number of scale points used and then multiplying by 7. We then meta-analyzed the means using the *metafor* package with random effects in R (Viechtbauer, 2010). We located four studies that reported the gender identification questionnaire, but two of these studies failed to include standard deviations. The remaining two studies, when meta-analytically combined, had a mean of 5.20 [95% CI: 4.74, 5.67], which placed the current mean of 5.10 inside the confidence interval. By contrast, we identified six studies using the math identification questionnaire, which had a meta-analytic mean of 4.73 [95% CI: 4.29, 5.16]. Our mean of 4.18 was lower than the lower bound of the confidence interval, indicating that our sample was somewhat less math identified than previous samples. However, one study (Gilbert, O’Brien, Garcia, & Marks, 2015) had a mean close to the value currently observed. Furthermore, the mean was above the mid-point of the seven-point scale, giving some evidence that math identification was not excessively low in the current sample.

Table 1

Studies in Mini Meta-Analysis of GIQ and MIQ scores

Author(s)	Year	Scale	<i>M</i>	<i>SD</i>	Scale	Item	<i>N</i>	Trans. <i>M</i>	Trans. <i>SD</i>
Cundiff, Vescio, Loken, & Lo	2013	GIQ	1.22	0.82	-2.5 to 2.5	4	876	5.51	0.96
Eriksson & Lindholm	2007	GIQ	3.45	NA	1 to 5	4	112	4.83	NA
Schmader	2002	GIQ	3.82	NA	1 to 5	4	32	5.35	NA
Wout, Danso, Jackson, & Spencer	2008	GIQ	4.83	1.17	1 to 7	4	59	4.83	1.17
Brown & Josephs	1999	MIQ	5.19	1.70	1 to 7*	5	33	5.19	1.70
Brown & Pinel	2003	MIQ	4.90	1.08	1 to 7	5	49	4.90	1.08
Gilbert, O'Brien, Garcia, & Marx	2015	MIQ	4.07	1.21	1 to 7	11	198	4.07	1.21
Inzlicht & Ben-Zeev	2003	MIQ	5.60	1.15	1 to 9	13	115	4.36	0.89
Inzlicht & Kang	2010	MIQ	5.37	1.40	1 to 7	5	34	5.37	1.40

Note. “GIQ” = Gender Identification Questionnaire (Luhtanen & Crocker, 1992; Schmader, 2000); “MIQ” = Math Identification Questionnaire; Trans. *M/SD* = Transformed Mean/Standard Deviation to a 7-point scale for comparison to our scale. * = Brown and Josephs (1999) did not state the number of scale points, but in later surveys Brown (& Pinel, 2003) used a 7-point scale. Given the *Ms* and *SDs* in this paper, we conclude that the authors likely used a 7-point scale for their analyses.

2.3 Participants

The full sample consisted of $N = 606$ individuals recruited from Mechanical Turk (Buhrmester, Kwang, & Gosling, 2011). We planned exclusions for analyses: participants had to be female, from the United States, and between the ages of 18-60 years ($N = 10$ participants did not meet these criteria). We also excluded participants who skipped more than five questions ($N = 6$) on the math test to ensure that the results were not impacted by participants who appeared to exert minimal effort in the study. The final sample contained $N = 590$ individuals, with an age

range of 18-60 ($M = 32.80$, $SD = 9.99$). Of those participants who indicated their race, 78.1% identified as White, 7.8% identified as Asian/Asian-American, 7.3% identified as Black/African-American, 4.2% indicated that they were a different race, and 1.0% indicated that they were Native American. Of these individuals, 6.9% identified as Hispanic or Latino. A small number of participants (1.5%) did not indicate their race.

Of those individuals who indicated their education level, 38.6% received a high school diploma/GED, 49.5% received a 2-/4-year college degree, and 11.7% received an advanced degree (e.g., M.D., J.D., Ph.D.). One participant did not indicate education level. Many participants indicated that they had previously taken standardized tests, specifically the SAT (48.5%), the ACT (31.9%), and the GRE (10.7%). Some participants (16.3%) were enrolled in an undergraduate or graduate program when they completed the study. In order to control for math experience, participants indicated how many years of math classes they had taken since their freshman year of high school; answers ranged from 0 to 20 years ($M = 4.93$, $SD = 2.41$). Usable SAT, ACT, and GRE tests scores were not reported for the majority of participants, so we were unable to consider achievement test scores as a control variable.

2.4 Procedure

The study was advertised through Mechanical Turk as a study of cognitive tasks (see <https://osf.io/wj26u/> for full posting). Participants who completed the pilot study were ineligible. Participants were compensated \$1.00 for taking part in the study. Users were redirected to an online survey website after giving their consent to participate.

To ensure that participants were able to hear the audio manipulation, participants first listened to a female voice state a key word (“television”) and were asked to choose the correct word from a list. If they did not select the correct word, participants were redirected to a page

explaining the necessity for having a computer that could play content from YouTube.com; participants who selected the correct answer were directed to a page that contained the main audio manipulation.

The audio manipulations were recorded in a female voice, using the same scripts from the tape-recorded instructions in Chalabaev et al., (2012). Participants randomly received one of six audio instructions for the test, in accordance with the 3 (Math Ability, Gender Differences, No Threat) $\times$ 2 (Performance Avoidance Goal, No Goal) design.

The instructions began with the stereotype threat/goal audio manipulations. After hearing the audio manipulation, participants read additional specific directions, which indicated that they could use a pencil and scratch paper and that they had one minute to complete each question, with four seconds in between each question (as in Chalebaev et al., 2012). Next, participants received the 10 GRE questions in random order. If participants did not answer a question after one minute, they were immediately advanced to the four second buffer screen and then the next question. Incomplete questions were scored as incorrect (however, results were similar even if the test was scored for accuracy, i.e., the number of questions correct out of the number of questions answered).

Manipulation checks were administered immediately following GRE questions. Participants answered an overt, open-ended item: “What type of ability does this test measure?” Participants then rated two items on a Likert scale from 1 (*strongly disagree*) to 7 (*strongly agree*): “The purpose of this task is to identify students who are exceptionally weak” (performance-avoidance goal) and “The purpose of this task is to identify students who are exceptionally strong” (performance-approach goal) These questions were identical to the manipulation checks used in Chalabaev et al. (2012).

After the manipulation checks, participants completed the Math Identity Questionnaire and the Gender Identity Questionnaire in a counterbalanced order; items within each of the questionnaires were also randomized. Following these two questionnaires, participants completed a demographic questionnaire.

2.5 Summary of Major Differences from Chalabaev et al. (2012)

The current study used a larger sample than Chalabaev et al.'s (2012) studies: $N = 590$ vs. $N = 86$ and $N = 58$. Chalabaev et al. used a 2 (threat present vs. threat absent) $\times$ 3 (goal type: performance avoidance, performance approach, and no goal) design in both studies. As detailed above, we compared performance avoidance goals to the no goal condition under one of two types of threat (group-concept vs. self-concept) or no threat.

Participants completed the basic procedure from Chalabaev et al.'s (2012) study before completing the math identity and gender identity measures; these measures were not collected in the original study. As noted above, the observed means for gender identification are consistent with other studies of stereotype threat. However, the current sample scored slightly lower on identification with math than other stereotype threat samples.

Participants were allowed to use scratch paper and a calculator, which was not allowed in the original. We used adult women participants and collected data online, whereas Chalabaev et al. (2012) collected data from exclusively undergraduate students in person at the University of California, Santa Barbara. Our participants were paid \$1 for their participation, whereas Chalabaev et al.'s participants were given course credit or \$10 for their participation. Chalabaev et al. additionally manipulated performance approach goals, but did not find a significant effect, and to simplify the design, we eliminated this factor from the design. We believe the replication to be fairly exact in all other ways.

3. Results

All statistical analyses were completed in R Statistical Software (Version 3.1.1), and the script for the analyses is available at <https://osf.io/xfs9d/>, and the data file itself is at <https://osf.io/pabns/>. 95% confidence intervals for effect sizes were calculated using the *compute.es* package in R (Del Re, 2014). Participants were randomly assigned to one out of six possible conditions (Math Ability/Performance Avoidance goal ($N = 103$), Math Ability/No goal ($N = 92$), Gender Differences/Performance Avoidance goal ($N = 102$), Gender Differences/No goal ($N = 90$), Neutral/Performance Avoidance goal ($N = 111$), Neutral/No goal ($N = 92$)). See Figure 1 for the means and 95% confidence intervals for math test performance in each condition.

Figure 1. Means and 95% Confidence Intervals for the Total Score on the Math Test by Condition.

3.1 Manipulation check

The first manipulation check was meant to ensure that the performance-avoidance goal manipulation was successful. Participants who received the manipulation should have agreed with the statement “The purpose of this test was to identify students who are exceptionally weak.” An independent samples *t*-test revealed that participants who were in the performance-avoidance goal condition ($M = 5.97$, $SD = 1.43$) agreed significantly more with the item than those who did not receive the manipulation ($M = 3.23$, $SD = 1.53$; Welch’s $t(561.47) = 22.24$, $p < .001$, $d = 1.84$, 95% CI = [1.64, 2.03]).

For the overt stereotype threat manipulation check item, two raters scored the responses, and the first author’s coding was used to score the items as math-related or non-math-related (Kappa = .98, 95% CI = [.97, 1.00]). We completed a Pearson’s chi-square test that indicated that those in the Math Ability condition were significantly more likely to indicate that the test measured math ability than those in the other two conditions, $\chi^2(1, N = 590) = 9.05$, $p = .003$, Odds Ratio = 1.57, 95% CI = [1.17, 2.11]. Conversely, those who did not receive any stereotype threat manipulation were significantly more likely to indicate that the test was a measure of problem-solving ability than those in the threat conditions, $\chi^2(1, N = 590) = 97.92$, $p < .001$, Odds Ratio = 5.04, 95% CI = [3.65, 6.95].

3.2 Task Performance

We hypothesized that there would be a crossover interaction, such that those in the performance-avoidance condition would perform better than those in the no goal condition when under stereotype threat, but would perform worse than those in the no goal condition in the neutral condition under no threat. We also hypothesized that the effect of threat would be stronger when threat was operationalized as group-concept threat (i.e., gender differences threat) compared to self-concept threat (i.e., math ability threat).

3.2.1 Predicted model. To test the 3 (Math Ability, Gender Differences, Neutral) $\times$ 2 (Performance Avoidance Goal, No Goal) model, we constructed a linear regression with one contrast coded variable that compared the two stereotype threat manipulations to the neutral (control) condition (-2 = Neutral, 1 = Gender Differences, 1 = Math Ability), one contrast coded variable that compared each of the stereotype threat conditions to each other (-1 = Gender Differences, 0 = Neutral, 1 = Math Ability), and a dummy coded variable for the goal manipulation (1 = performance-avoidance goal; 0 = no goal). This method was chosen to enable a test of the main effect of stereotype threat across the two threat conditions, as well as a comparison of the two threat types.

When entered into a linear model, the model revealed no significant main or interaction effects (see Table 2; see Figure 2 for effect size comparison between current study and Chalabaev et al., 2012, for threatened participants' performance under performance avoidance goals vs. no goals).

Table 2

Regression Model Predicting GRE Score with No Controls

Variable	<i>b</i>	<i>SE b</i>	<i>t</i>	<i>p</i>
(Intercept)	4.41	0.13	32.83	< .001
Contrast 1 – ST vs. No Threat (A)	-0.12	0.09	-1.26	.21
Performance Avoidance Goals (B)	-0.17	0.18	-0.92	.36
Contrast 2 – SC Threat vs. GC Threat (C)	-0.16	0.16	-0.99	.33
A x B	0.08	0.13	0.58	.56
B x C	0.14	0.23	0.61	.55

Note. Model $df = 584$. ST = Stereotype Threat; SC Threat = self-concept threat; GC Threat = group-concept threat. $R^2 = .01$ (R^2 adjusted = .00).

The performance boost for those induced with performance-avoidance goals under math ability

threat was far weaker in our study ($d = 0.08$, 95% CI = $[-0.20, 0.37]$) than the effect size ($d = 0.72$, 95% CI = $[-0.02, 1.45]$) found in Chalabaev et al. (2012). The effect size for the performance-avoidance goal/no goal comparison under gender differences threat ($d = -0.13$, 95% CI = $[-0.42, 0.15]$) was in the opposite direction as, and much smaller than, the effect size ($d = 0.78$, 95% CI = $[-0.13, 1.69]$) found by Chalabaev et al.

Figure 2. Effect sizes for the Current Study and Chalabaev et al. (2012). Effect sizes compare performance for threatened participants under performance avoidance goal vs. no goal for self-concept threat (top panel) and group-concept threat (bottom panel). Values for Chalabaev et al. (2012) calculated based on means and standard deviations reported in their Table 1.

The main effect of stereotype threat was similarly weak in our sample; the math ability main effect size was small ($d = -0.13$, 95% CI = $[-0.32, 0.07]$), as was the gender differences main effect size ($d = -0.02$, 95% CI = $[-0.19, 0.16]$). The observed effect size in our sample is much smaller than in some other studies on stereotype threat, but Flore and Wicherts (2015) estimated that the average effect size of stereotype threat is equal to -0.22 for girls under age 18. Although our sample was composed of adult women, our data converges with Flore and Wicherts' estimate, showing that the effect size of stereotype threat probably smaller than previously supposed.

3.2.2 Controls. We ran the predicted regression model several times with different controls for math experience and other variables that may have moderated stereotype threat effects. Indeed, the students in our sample were significantly more math identified than non-students ($t(147.81) = 2.345$, $p = .02$). If math identification is important for observing stereotype threat effects, we expect student status, or math identification directly, to moderate the size of effects. Additionally, age could serve as another proxy for math identification (however, neither gender identification ($r = .09$) nor math identification ($r = -.02$) correlated with age in our sample). Regardless, we tested these variables (math identification, student status, and age) for interaction effects.

None of these controls had significant interaction effects with the stereotype threat or achievement goal manipulations, including education level (see Supplementary Tables). None of the main effects for these variables were significant except for education level (see Table 3; more educated students performed better on the math test than less educated students). Controlling math identity and gender identity also failed to reveal any significant effects, although math identification was the best predictor of math performance ($b = 0.508$, $t(588) = 7.776$, $p < .001$)

on its own. There was a marginally significant three-way interaction between education level, stereotype threat, and achievement goal manipulations ($p = .07$). However, as depicted in the supplemental materials (Supplemental Figure 2), the interpretation of the interaction was unclear, with results showing a mix of small beneficial and detrimental effects of various combinations of threat and avoidance goals. There was also a marginal three-way interaction with student status, such that *non-students* showed some evidence of threat effects, but only in the absence of a performance avoidance goal (see Supplemental Table 3). At the risk of over interpreting noise, and in the absence of a clear pattern of results, we did not probe these marginal interactions further. The supplemental materials and the OSF page (<https://osf.io/jze8c/>) contain regression tables for math and gender identity, as well as other supplemental tables. See Table 4 for inter-correlations between the different control variables.

We considered the possibility of floor effects on the math test in exploratory analyses, but the distribution of math performance did not suggest a floor effect. Further we repeated analyses while removing participants who scored 0 out of 10 ($N = 18$), and we found little evidence of changes in the results (Johnson, Cheung, & Donnellan, 2014). The results do not appear to be impacted by floor effects.

Table 3

Regression Model Predicting GRE Score with Education Level as Control

Variable	<i>b</i>	<i>SE b</i>	<i>t</i>	<i>p</i>
(Intercept)	4.02	0.22	18.52	< .001
Contrast 1 - ST vs. No Threat (A)	-0.29	0.16	-1.78	.08
Performance Avoidance Goal (B)	-0.21	0.29	-0.71	.48

Education level

HS Degree versus College (C)	0.58	0.29	2.01	.04
HS Degree versus > College (D)	1.06	0.47	2.25	.02
Contrast 2 - SC Threat vs. GC Threat (E)	-0.06	0.25	-0.22	.82
A x B	0.39	0.21	1.83	.07
A x C	0.23	0.20	1.12	.26
A x D	0.51	0.35	1.48	.14
B x C	-0.07	0.39	-0.19	.85
B x D	0.37	0.62	0.60	.55
B x E	-0.27	0.35	-0.77	.44
C x E	-0.17	0.35	-0.50	.62
D x E	0.16	0.55	0.28	.78
A x B x C	-0.51	0.28	-1.84	.07
A x B x D	-0.64	0.44	-1.44	.15
A x C x E	0.55	0.48	1.15	.25
B x D x E	0.63	0.74	0.86	.39

Note. Model $df = 571$. HS = High School; ST = Stereotype Threat; SC Threat = self-concept threat; GC Threat = group-concept threat. $R^2 = .06$ (R^2 adjusted = .03).

Table 4

Inter-Correlations between Control Variables

	1	2	3	4	5	6	7
1. # of Standardized Tests	1.00						
2. Years of Math	.19	1.00					
3. Education Level	.33	.24	1.00				
4. Math Identity	.14	.10	.18	1.00			
5. Age	-.17	-.06	.07	-.03	1.00		
6. Gender Identity	.14	.00	.15	.15	.10	1.00	
7. Student Status	-.13	-.03	.13	-.09	.35	.02	1.00

4. Discussion

The current study aimed to assess the impact of different types of stereotype threat in a large sample of adult women and to determine if inducing performance-avoidance goals improves performance under threat. Our results indicate a failure to replicate Chalabaev et al. (2012), with no evidence suggesting the presence of significant stereotype threat main effects, nor any moderation by performance avoidance goals, in spite of the fact that the current replication study had a much larger sample size than the original study.

Although performance-avoidance goals were theorized to bolster performance under stereotype threat, no significant main or interaction effects of performance-avoidance goals emerged. Several controls for math experience, math identification, gender identification, education level, and age were also considered, none of which revealed any significant main or interaction effects. We did observe a lower average level of math identification in the current sample than other studies of stereotype threat, which may have inhibited our ability to observe the effect. However, we did not observe any moderation of the main effect by math identification or other similar variables (e.g., age). Further, Nguyen and Ryan (2008) suggest that moderately math-identified women are affected more strongly by stereotype threat than strongly math-identified women, indicating that our sample would be adequately identified with math to observe the effect. We cannot rule out low math identification as the mechanism behind our null effects, but the lack of consensus in the literature about the role of domain identification in stereotype threat suggests future research in this area may be warranted.

The current findings are not the first to cast doubt on the magnitude of the stereotype threat effect. Stoet and Geary (2012) found that 55% of 21 studies that attempted to replicate Spencer et al. (1999) produced a significant interaction effect between gender and stereotype

threat. Half of the successful effects used SAT scores as a covariate, but only 30% of studies that did not use SAT scores as a covariate replicated the effect. It should be noted that Spencer et al. did not use SAT score as a control, and they still found an effect of stereotype threat. We used years of math education as a control for math ability, but found no moderating effects of this variable on our results. The inclusion of various controls for math ability is not uncontroversial (Stoet & Geary, 2012), but nonetheless, with or without control variables, we found no evidence for the basic effect.

Publication bias has been cited as the cause of discrepancies in results between small sample studies and larger replications (such as the current study) in the domain of stereotype threat. Flore and Wicherts (2015) estimated the effect size of stereotype threat on the performance of adolescent girls in stereotyped domains to be $d = -0.22$. They suggest that publication bias has overinflated the effect size of stereotype threat (Flore & Wicherts, 2015). Publication bias refers to the fact that studies with null findings are often neither written up nor accepted for publication by many top journals (Begg, 1994). They recommended a large-scale replication study to test the stereotype threat hypothesis, and the current research fulfills that request. Incorporating the present study into the meta-analysis would serve to further shrink this effect size estimate (see Figure 2).

Although the current study consists of a large sample replication, some may attribute the null results to the fact that our participants were not undergraduate students, which may make them less vulnerable to stereotype threat. Many stereotype threat studies use samples composed of undergraduate students, a fact that may lead researchers to overgeneralize stereotype threat to populations of non-students. Although students ($N = 97$) performed better on the GRE test questions compared to non-students and identified more with math, none of the predicted effects

were significant for students (conversely, in the no-goal condition we found some limited evidence for a threat effect in non-students). Additionally, because our sample was comprised of Mechanical Turk workers, others may assume that participants did not care about the test, which would make the effect of stereotype threat more difficult to detect (Steele & Aronson, 1995). There is no evidence, given our manipulation checks and our participants' test results, that our sample cared less about the math test than a sample of undergraduates participating in a study.

Others will likely question the ability of the stereotype threat manipulations to generalize to an online context, especially given that participants in our study completed the math questions outside of the lab without the threat of immediate evaluation by the experimenter, which could potentially dampen threat effects. Despite this doubt, standardized tests are increasingly being administered in computerized formats, so it is important to examine the effect of threat manipulations under non-laboratory conditions (Noyes & Garland, 2008). At the very least, the current study provides evidence to question the generalizability of stereotype threat effects beyond female undergraduate samples tested in laboratory settings.

All told, the current results question not only the ability of performance-avoidance goals to improve performance under threat, but also the generalizability of stereotype threat effects for women in mathematics. Other researchers have suggested that social psychologists have not scrutinized stereotype threat as heavily as other theories, partly because of its usefulness in explaining the STEM gender gap (Flore & Wicherts, 2015; Stoet & Geary, 2012). Stoet and Geary (2012) call for a more critical reading of the stereotype threat literature to question the belief that a causal relationship exists between stereotype threat and worsened math performance.

The present study provides substantial evidence to question the definition and

operationalization of stereotype threat and the validity of potential moderators of stereotype threat. Policymakers rely on social psychologists to provide insight into the nature of issues like the gender gap in STEM fields in order to ensure that interventions aimed at closing this gap are effective (Stoet & Geary, 2012). Should policymakers continue to view stereotype threat as the *principal* cause of the STEM gender gap, there may be an opportunity cost as potentially less effective interventions are pursued instead of more beneficial measures (Nguyen & Ryan, 2008; Stoet & Geary, 2012).

Multiple researchers have cited the need for quality replications of published results, especially in social psychology, in large cross-cultural samples (Roediger, 2012; Flore & Wicherts, 2015). We do not conclude that stereotype threat has no effect on performance in every context, but instead we suggest that the effect of existing threat cues may not have as strong an impact on performance as previously thought.

In order to more effectively close the gender gap in STEM fields, we suggest that researchers investigate other explanations beyond stereotype threat that can explain discrepancies in men's and women's math performance, such as the inability to fulfill communal goals and the environment of workplaces in STEM that may discriminate against women who choose to have a family and desire more flexible hours (Diekmann, Clark, Johnston, Brown, & Steinberg 2011; Heilbrunner, 2013). Although stereotype threat is an appealing answer to the question of what causes the gender gap in STEM, we advise that researchers not rely solely on literature that may be skewed by inflated effect sizes and small samples.

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. Informed consent was obtained from all individual participants included in the study.

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Supplemental Materials to Accompany “Do Performance Avoidance Goals Moderate the Effect of Different Types of Stereotype Threat on Women’s Math Performance?”

Katherine M. Finnigan, Katherine S. Corker

April 27, 2016

Contents

These supplemental materials contain details about the pilot study (pp. 1-6), supplementary tables and figures to accompany the main manuscript (pp. 7-17), and the full text of the manipulations (pp. 18-19).

Pilot Study: Method

Participants

The sample consisted of $N = 62$ American females, aged 19-60 ($M = 37.62$, $SD = 11.76$). We excluded participants who skipped more than five questions on any given test, and one participant met this criterion; the final sample was equal to $N = 61$. Of those who indicated their ethnicity, 81.4% of participants identified as White, 8.5% identified as Asian-American, 6.8% identified as African-American, 1.7% identified as Native American, and 1.7% selected another race. Two participants (3.3%) identified as Hispanic or Latino. A small number of participants did not list English as their first language (3.3%).

Participants were well-educated; 41.9% of participants earned a high school diploma/GED, 32.3% of participants earned a degree from a 2-year or 4-year institution, and 25.8% participants earned an advanced degree (e.g., JD, MD, PhD). Many of the participants were familiar with standardized tests, as 35 (55.7%) participants had taken the SAT, 15 (24.6%) participants had taken the ACT, and 10 (16.1%) participants had taken the GRE. Ten (16.4%) participants stated that they were currently pursuing a graduate or undergraduate degree. In order

to control for math experience, participants were asked to report how many years of math education they had received since beginning high school; the number of years indicated by participants ranged from 0-16 years ($M = 4.74$, $SD = 3.66$).

Materials

In order to assess the appropriate difficulty for a test of math performance under stereotype threat, we included three tests of increasing difficulty level. Each of these tests included 10 multiple-choice questions.

Sixth grade level – California Standards Test. The test with the lowest difficulty level consisted of 10 publicly released questions from California Standards Test (CST; California Department of Education, 2009), which is annually administered to sixth graders in the state of California as a part of the Standardized Testing and Reporting Program. The questions covered a variety of topics in mathematics, and participants were given four response options per question.

High school level – Nevada High School Proficiency Examination. Participants also received the Nevada High School Proficiency Examination (HSPE; Nevada State Department of Education, 1999), a test that is annually administered to tenth grade students in the state of Nevada. Like the CST, the ten questions that participants received were selected from a larger set of released questions and covered various mathematics domains. The questions were in a multiple choice format with five response options per question.

Post-secondary level – Graduate Records Examination. The most difficult set of questions came from a practice test for the quantitative reasoning section of the Graduate Readiness Examination (GRE; Kaplan Publishing, 2007). We administered the same GRE questions used in Chalabaev et al. (2012), who supplied us with the questions they used. The questions were in multiple-choice format with five response options per question.

Procedure

The study was advertised through Mechanical Turk, a partner website of Amazon.com that allows people to sign up to complete online tasks including surveys (Buhrmester, Kwang, & Gosling, 2011). The study was advertised as a survey of cognitive tasks, and the posting indicated that we sought females in the United States, aged 18-60. Participants had to be registered users of the site and were compensated \$1.00 each for taking part in the study. Users were redirected to an online survey website after giving their consent to participate.

After electronically signing a consent form, participants were shown a YouTube clip of a female voice saying a key word (“television”) and repeating it twice. Afterwards, participants were given a list of 10 words and were asked to select the spoken word from the clip; participants could also indicate that they did not hear the clip or could not play the video. We included this question to ensure that the audio manipulations in the main study would work across multiple web browsers and computing systems.

Regardless of whether or not the participant heard the audio clip, they were shown the 30 test questions in random order. There was a four-second break between each question, and participants had one minute to answer each question. This procedure is identical to the procedure used in Chalabaev et al. (2012), except that this survey was not administered in-person.

Following the test questions, participants received a brief demographics questionnaire, with a final question asking them to confirm their gender. They were shown a debriefing form detailing the purpose of the study.

Pilot Study: Results

All statistical analyses were completed in R Statistical Software (Version 3.1.1), and the script for the analyses is available on the Open Science Framework page for the study

(<https://osf.io/kvyhb>). The pilot study was intended to identify the optimum test difficulty level for Mechanical Turk workers. Two test item characteristics were considered in these analyses: item discrimination and item difficulty. Test item discrimination is defined as “the degree to which a test item differentiates people who score high on the total test from those who score low on the total test” (Furr & Bacharach, 2013, p. 189). Item discrimination is often represented by the correlation between an individual test item and the total test score. A high item-total correlation is a desirable attribute of a test because it indicates that performance on the item is consistent with performance on the test as a whole. We did a Fisher’s r -to- z transformation of each item-total correlation, then took the average of the transformed scores, and converted the scores back to Pearson r values (GRE: $r = .40$; HSPE: $r = .49$; CST: $r = .55$). Although all three tests had fairly similar average item-total correlations, the CST had the highest average item discrimination.

Test difficulty is described by the mean score on an item, which indicates how many participants answered the item correctly. For example, if the mean score on a binary item is $M = .20$, that means that 20% of participants answered the question correctly; 20% of participants is relatively low, so we would categorize this item as a high difficulty item. For each test type, we took the average item mean for the 10 items; lower means indicate higher difficulty levels for each test item on average (GRE: $M = 0.42$, $SD = 0.19$; HSPE: $M = 0.51$, $SD = 0.23$; CST: $M = 0.71$, $SD = 0.23$). As expected, the GRE was the most difficult test for Mechanical Turk workers, followed by the HSPE and the CST.

We also calculated the raw Cronbach’s alphas for each test type (GRE: $\alpha = .43$; HSPE: $\alpha = .69$; CST: $\alpha = .73$). Cronbach’s alpha estimates the internal consistency of a test. The CST and the HSPE had high alpha coefficients, indicating good reliability, within the sample. The GRE

had a lower alpha coefficient, indicating moderate reliability. If we remove the ninth test item from the GRE which had the lowest item-test correlation value ($r = .23$), the alpha for the GRE test increases to $\alpha = .49$.

Pilot Study: Discussion

This study was meant to evaluate the average math ability of American, female Mechanical Turk workers between the ages of 18 and 60. In order to ensure that the GRE test items used in Chalabaev et al. (2012) were of an appropriate difficulty level for Mechanical Turk workers, we administered a Pilot Study to female adult Mechanical Turk workers that contained three math tests at three levels of difficulty. Previous research indicates that the effect of stereotype threat is the most detrimental to performance when the test is difficult (Spencer, Steele, & Quinn, 1999), thus test item difficulty and item discrimination were the most important measures of test utility in my analysis.

As expected, the GRE was the most difficult of the three tests, and it had an average item-total correlation that slightly lower than the HSPE or the CST. However, we do not believe that the GRE was substantially less reliable than the other two tests. Although the ninth test item on the GRE had a low item-total correlation, we kept it in the test in order to ensure that the analyses are directly comparable to Chalabaev et al. (2012). Additionally, the difficulty level of the test was slightly below 50%, which we believe is the appropriate level at which the effect of stereotype threat is theorized to exist (Senko & Harackiewicz, 2005). In order to adhere as close as possible to the original methods in Chalabaev et al. (2012), we chose the GRE as the measure of math test performance for the Main Study.

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Table S1

Means, Standard Deviations, and Item-Total Correlation for GRE Test Items

	Pilot Test			Main Test		
	<i>M</i>	<i>SD</i>	<i>r</i>	<i>M</i>	<i>SD</i>	<i>r</i>
Item 1	0.60	0.49	.38	0.54	0.50	.53
Item 2	0.35	0.48	.67	0.45	0.50	.60
Item 3	0.48	0.50	.44	0.50	0.50	.49
Item 4	0.55	0.50	.31	0.57	0.50	.43
Item 5	0.38	0.49	.47	0.44	0.50	.49
Item 6	0.48	0.50	.44	0.60	0.49	.50
Item 7	0.32	0.47	.24	0.36	0.48	.29
Item 8	0.59	0.50	.49	0.59	0.49	.54
Item 9	0.23	0.43	.18	0.41	0.49	.44
Item 10	0.22	0.42	.29	0.25	0.43	.37

Table S2

Regression Model Predicting GRE Score with Years of Math Education as Control

Variable	<i>b</i>	<i>SE b</i>	<i>t</i>	<i>p</i>
(Intercept)	4.42	0.14	32.51	< .01
Contrast 1 - ST vs. No Threat (A)	-0.12	0.10	-1.24	.22
Performance Avoidance Goal (B)	-0.17	0.19	-0.90	.37
Years of math - Centered (C)	-0.05	0.06	-0.75	.45
Contrast 2 - SC Threat vs. GC Threat (D)	-0.14	0.17	-0.86	.39
A x B	0.08	0.13	0.62	.53
A x C	-0.01	0.04	-0.17	.86
B x C	0.01	0.08	0.09	.93
B x D	0.10	0.23	0.44	.66
C x D	0.12	0.08	1.46	.15
A x B x C	-0.02	0.06	-0.39	.70
B x C x D	-0.03	0.10	-0.30	.77
R^2		0.02		
R^2 adjusted		0.00		
<i>df</i>		571		

Note. ST = Stereotype Threat; SC Threat = self-concept threat; GC Threat = group-concept threat.

Table S3

Regression Model Predicting GRE Score with Student Status as a Factor

Variable	<i>b</i>	<i>SE b</i>	<i>t</i>	<i>p</i>
(Intercept)	4.34	0.15	29.07	< .001
Contrast 1 - ST vs. No Threat (A)	-0.21	0.11	-1.98	.05
Performance Avoidance Goal (B)	-0.21	0.20	-1.06	.29
Student Status (C)	0.27	0.35	0.79	.43
Contrast 2 - SC Threat vs. GC Threat (D)	-0.20	0.18	-1.10	.27
A x B	0.21	0.14	1.46	.15
A x C	0.48	0.25	1.93	.05
B x C	0.56	0.51	1.10	.27
B x D	0.15	0.25	0.59	.56
C x D	0.26	0.41	0.63	.53
A x B x C	-0.61	0.35	-1.74	.08
B x C x D	0.03	0.63	0.05	.96
R^2		0.03		
R^2 adjusted		0.01		
<i>df</i>		570		

Note. ST = Stereotype Threat; SC Threat = self-concept threat; GC Threat = group-concept threat.

Table S4

Regression Model for Predicting GRE Score with Number of Standardized Tests as Control

Variable	<i>b</i>	<i>SE b</i>	<i>t</i>	<i>p</i>
(Intercept)	4.15	0.20	20.76	< .01
Contrast 1 – ST vs. No Threat (A)	-0.16	0.14	-1.17	.24
Performance Avoidance goal (B)	-0.53	0.28	-1.88	.06
Number of standardized tests (C)	0.31	0.17	1.80	.07
Contrast 2 – SC Threat vs. GC Threat (D)	-0.23	0.25	-0.92	.36
A × B	0.17	0.20	0.88	.38
A × C	0.05	0.12	0.39	.70
B × C	0.34	0.24	1.42	.16
B × D	-0.08	0.35	-0.23	.82
C × D	0.11	0.21	0.52	.60
A × B × C	-0.10	0.17	-0.62	.54
B × C × D	0.15	0.29	0.52	.60
<i>R</i> ²		0.04		
<i>R</i> ² adjusted		0.02		
<i>df</i>		578		

Note. ST = Stereotype Threat; SC Threat = self-concept threat; GC Threat = group-concept threat.

Table S5

Regression Model for Predicting GRE Score with Math Identity Questionnaire Score as Control

Variable	<i>b</i>	<i>SE b</i>	<i>t</i>	<i>p</i>
(Intercept)	4.40	0.13	34.08	< .001
Contrast 1 – ST vs. No Threat (A)	-0.09	0.09	-1.02	.31
Performance Avoidance goal (B)	-0.14	0.18	-0.81	.42
MIQ - Centered (C)	0.43	0.10	4.35	< .001
Contrast 2 - SC Threat vs. GC Threat (D)	-0.22	0.16	-1.38	.17
A × B	0.11	0.12	0.91	.37
A × C	-0.04	0.07	-0.64	.53
B × C	0.14	0.13	1.02	.31
B × D	0.24	0.22	1.09	.28
C × D	0.00	0.12	-0.03	.98
A × B × C	-0.03	0.09	-0.34	.74
B × C × D	0.11	0.17	0.67	.51
R^2		0.11		
R^2 adjusted		0.09		
<i>df</i>		578		

Note. ST = Stereotype Threat; SC Threat = self-concept threat; GC Threat = group-concept threat; “MIQ” = Math Identity Questionnaire Score; *p*-values below 0.05 are statistically significant.

Table S6

*Regression Model for Predicting GRE Score with Gender Identity Questionnaire Score as**Control*

Variable	<i>b</i>	<i>SE b</i>	<i>t</i>	<i>p</i>
(Intercept)	4.39	0.14	32.36	< .01
Contrast 1 - Stereotype Threat (A)	-0.09	0.10	-0.95	.35
Performance Avoidance goal (B)	-0.15	0.19	-0.79	.43
GIQ - Centered (C)	-0.06	0.10	-0.55	.58
Contrast 2 - Stereotype Threat (D)	-0.16	0.17	-1.00	.32
A × B	0.03	0.13	0.23	.82
A × C	0.05	0.07	0.68	.50
B × C	0.08	0.14	0.55	.58
B × D	0.16	0.23	0.71	.48
C × D	-0.07	0.12	-0.59	.55
A × B × C	0.06	0.10	0.64	.52
B × C × D	-0.05	0.17	-0.31	.76
<i>R</i> ²		0.01		
<i>R</i> ² adjusted		0.00		
<i>df</i>		578		

Note. ST = Stereotype Threat; SC Threat = self-concept threat; GC Threat = group-concept threat; “GIQ” = Gender Identity Questionnaire Score; *p*-values below 0.05 are statistically significant.

Table S7

Regression Model Predicting GRE Score with Age as Control

Variable	<i>b</i>	<i>SE b</i>	<i>t</i>	<i>p</i>
(Intercept)	4.41	0.13	33.03	< .01
Contrast 1 - ST vs. No Threat (A)	-0.12	0.09	-1.29	.20
Performance Avoidance Goal (B)	-0.17	0.18	-0.94	.35
Age - Centered (C)	-0.01	0.01	-0.76	.45
Contrast 2 - SC Threat vs. GC Threat (D)	-0.16	0.16	-1.00	.32
A x B	0.06	0.13	0.49	.63
A x C	0.00	0.01	-0.04	.97
B x C	-0.04	0.02	-1.96	.05
B x D	0.16	0.23	0.70	.49
C x D	-0.01	0.02	-0.61	.54
A x B x C	0.00	0.01	0.07	.94
B x C x D	0.01	0.02	0.43	.67
R^2		0.03		
R^2 adjusted		0.01		
<i>df</i>		578		

Note. ST = Stereotype Threat; SC Threat = self-concept threat; GC Threat = group-concept threat.

Table S8

Regression Model Predicting GRE Score with Student Status as a Factor

Variable	<i>b</i>	<i>SE b</i>	<i>t</i>	<i>p</i>
(Intercept)	4.34	0.15	29.07	< .001
Contrast 1 - ST vs. No Threat (A)	-0.21	0.11	-1.98	.05
Performance Avoidance Goal (B)	-0.21	0.20	-1.06	.29
Student Status (C)	0.27	0.35	0.79	.43
Contrast 2 - SC Threat vs. GC Threat (D)	-0.20	0.18	-1.10	.27
A x B	0.21	0.14	1.46	.15
A x C	0.48	0.25	1.93	.05
B x C	0.56	0.51	1.10	.27
B x D	0.15	0.25	0.59	.56
C x D	0.26	0.41	0.63	.53
A x B x C	-0.61	0.35	-1.74	.08
B x C x D	0.03	0.63	0.05	.96
R^2			0.03	
R^2 adjusted			0.01	
<i>df</i>			570	

Note. ST = Stereotype Threat; SC Threat = self-concept threat; GC Threat = group-concept threat.

Table S9

Regression Model for Predicting GRE Score with All Control Variables

Variable	<i>b</i>	<i>SE b</i>	<i>t</i>	<i>p</i>
(Intercept)	2.47	0.64	3.88	< .001
Number of standardized tests	0.26	0.12	2.12	.03
Education level	0.56	0.15	3.86	< .001
Years of math - Centered	-0.13	0.04	-3.43	< .001
MIQ	0.47	0.07	6.95	< .001
Age - Centered	-0.02	0.01	-2.28	.02
GIQ	-0.14	0.07	-2.07	.04
Student status	-0.31	0.25	-1.22	.22
Contrast 1 – ST vs. No Threat (A)	-0.09	0.09	-0.98	.33
Performance Avoidance Goals (B)	-0.08	0.17	-0.48	.63
Contrast 2 – SC Threat vs. GC Threat (C)	-0.20	0.15	-1.29	.20
A × B	0.10	0.12	0.79	.43
B × C	0.15	0.21	0.71	.48
R^2		0.16		
R^2 adjusted		0.14		
<i>df</i>		565		

Note. ST = Stereotype Threat; SC Threat = self-concept threat; GC Threat = group-concept threat; “MIQ” = Math Identity Questionnaire Score; “GIQ” = Gender Identity Questionnaire; *p*-values below 0.05 are statistically significant.

Figure S1. Means and 95% Confidence Intervals of Total GRE Score in the Pilot and Main Studies

Figure S2. Means for Total GRE Score for All Conditions by Education Level.

Appendix

Script for Audio Instructions

Math Ability/Performance Avoidance goal:

“You are going to perform a math test. The particular test you will be taking today is designed to help us identify people who are exceptionally weak in their mathematical reasoning abilities. Your performance on this test will not be scored like most normal tests, but rather will be classified as either above or below a predetermined cutoff score. If you score below the cutoff score, this suggests you are exceptionally weak. In other words, significantly below average in your mathematical reasoning abilities. However, scoring above the cutoff score tells us little or nothing about your mathematic abilities or math potential. You may be slightly below average, average, or even above average. Thus, this test and the scoring method used with it are designed only to separate those who are exceptionally weak from everyone else. At the end of the test you will be provided with information regarding how you did on the math test compared with other participants.”

Math ability/No goal:

“You are going to perform a math test.”

Gender Differences/Performance Avoidance goal:

“As you probably know, math skills are crucial to performance in many important subjects. Previous research has sometimes shown gender differences in math ability and sometimes shown no gender differences. The test you are about to take has been shown to produce gender differences. The particular test you will be taking today is designed to help us identify people who are exceptionally weak in their mathematical reasoning abilities. Your performance on this test will not be scored like most normal tests, but rather will be classified as either above or below a predetermined cutoff score. If you score below the cutoff score, this suggests you are exceptionally weak. In other words, significantly below average in your mathematical reasoning abilities. However, scoring above the cutoff score tells us little or nothing about your mathematic abilities or math potential. You may be slightly below average, average, or even above average. Thus, this test and the scoring method used with it are designed only to separate those who are exceptionally weak from everyone else. At the end of the test you will be provided with information regarding how you did on the math test compared with other participants.”

Gender Differences/No goal:

“As you probably know, math skills are crucial to performance in many important subjects. Previous research has sometimes shown gender differences in math ability and sometimes shown no gender differences. The test you are about to take has been shown to produce gender differences.”

Neutral/Performance Avoidance goal:

“You are going to perform a problem-solving test. The particular test you will be taking today is designed to help us identify people who are exceptionally weak in their mathematical reasoning abilities. Your performance on this test will not be scored like most normal tests, but rather will be classified as either above or below a predetermined cutoff score. If you score below the cutoff score, this suggests you are exceptionally weak. In other words, significantly below average in your mathematical reasoning abilities. However, scoring above the cutoff score tells us little or nothing about your mathematic abilities or math potential. You may be slightly below average, average, or even above average. Thus, this test and the scoring method used with it are designed only to separate those who are exceptionally weak from everyone else. At the end of the test you will be provided with information regarding how you did on the math test compared with other participants.”

Neutral/No goal:

“You are going to perform a problem-solving test.”

Table 1

Studies in Mini Meta-Analysis of GIQ and MIQ scores

Author(s)	Year	Scale	<i>M</i>	<i>SD</i>	Scale	Item	<i>N</i>	Trans. <i>M</i>	Trans. <i>SD</i>
Cundiff, Vescio, Loken, & Lo	2013	GIQ	1.22	0.82	-2.5 to 2.5	4	876	5.51	0.96
Eriksson & Lindholm	2007	GIQ	3.45	NA	1 to 5	4	112	4.83	NA
Schmader	2002	GIQ	3.82	NA	1 to 5	4	32	5.35	NA
Wout, Danso, Jackson, & Spencer	2008	GIQ	4.83	1.17	1 to 7	4	59	4.83	1.17
Brown & Josephs	1999	MIQ	5.19	1.70	1 to 7*	5	33	5.19	1.70
Brown & Pinel	2003	MIQ	4.90	1.08	1 to 7	5	49	4.90	1.08
Gilbert, O'Brien, Garcia, & Marx	2015	MIQ	4.07	1.21	1 to 7	11	198	4.07	1.21
Inzlicht & Ben-Zeev	2003	MIQ	5.60	1.15	1 to 9	13	115	4.36	0.89
Inzlicht & Kang	2010	MIQ	5.37	1.40	1 to 7	5	34	5.37	1.40

Note. “GIQ” = Gender Identification Questionnaire (Luhtanen & Crocker, 1992; Schmader, 2000); “MIQ” = Math Identification Questionnaire; Trans. *M/SD* = Transformed Mean/Standard Deviation to a 7-point scale for comparison to our scale. * = Brown and Josephs (1999) did not state the number of scale points, but in later surveys Brown (& Pinel, 2003) used a 7-point scale. Given the *Ms* and *SDs* in this paper, we conclude that the authors likely used a 7-point scale for their analyses.

Table 2

Regression Model Predicting GRE Score with No Controls

Variable	<i>b</i>	<i>SE b</i>	<i>t</i>	<i>p</i>
(Intercept)	4.41	0.13	32.83	< .001
Contrast 1 – ST vs. No Threat (A)	-0.12	0.09	-1.26	.21
Performance Avoidance Goals (B)	-0.17	0.18	-0.92	.36
Contrast 2 – SC Threat vs. GC Threat (C)	-0.16	0.16	-0.99	.33
A x B	0.08	0.13	0.58	.56
B x C	0.14	0.23	0.61	.55

Note. Model $df = 584$. ST = Stereotype Threat; SC Threat = self-concept threat; GC Threat = group-concept threat. $R^2 = .01$ (R^2 adjusted = .00).

Table 3

Regression Model Predicting GRE Score with Education Level as Control

Variable	<i>b</i>	<i>SE b</i>	<i>t</i>	<i>p</i>
(Intercept)	4.02	0.22	18.52	< .001
Contrast 1 - ST vs. No Threat (A)	-0.29	0.16	-1.78	.08
Performance Avoidance Goal (B)	-0.21	0.29	-0.71	.48
Education level				
HS Degree versus College (C)	0.58	0.29	2.01	.04
HS Degree versus > College (D)	1.06	0.47	2.25	.02
Contrast 2 - SC Threat vs. GC Threat (E)	-0.06	0.25	-0.22	.82
A x B	0.39	0.21	1.83	.07
A x C	0.23	0.20	1.12	.26
A x D	0.51	0.35	1.48	.14
B x C	-0.07	0.39	-0.19	.85
B x D	0.37	0.62	0.60	.55
B x E	-0.27	0.35	-0.77	.44
C x E	-0.17	0.35	-0.50	.62
D x E	0.16	0.55	0.28	.78
A x B x C	-0.51	0.28	-1.84	.07
A x B x D	-0.64	0.44	-1.44	.15
A x C x E	0.55	0.48	1.15	.25
B x D x E	0.63	0.74	0.86	.39

Note. Model $df = 571$. HS = High School; ST = Stereotype Threat; SC Threat = self-concept threat; GC Threat = group-concept threat. $R^2 = .06$ (R^2 adjusted = .03).

Table 4

Inter-Correlations between Control Variables

	1	2	3	4	5	6	7
1. # of Standardized Tests	1.00						
2. Years of Math	.19	1.00					
3. Education Level	.33	.24	1.00				
4. Math Identity	.14	.10	.18	1.00			
5. Age	-.17	-.06	.07	-.03	1.00		
6. Gender Identity	.14	.00	.15	.15	.10	1.00	
7. Student Status	-.13	-.03	.13	-.09	.35	.02	1.00

Figure 1
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Figure 2
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