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Fitting In Across STEM: Comparing Science/Math and Engineering/Technology Students' Perceptions of Their Fields and Futures

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Introduction

Increasing the recruitment and retention of students into STEM has been a goal of the field for some time now [1]–[3]. Not only are more STEM majors still needed to meet projected employment goals, but there remain ongoing issues with representation and diversity [4]–[6]. Confronting these issues and recruiting more equally from marginalized groups (such as women and racial minorities) can help solve the numbers problem and can improve the quality of work being done [7], [8]. This requires both expanded efforts to engage new students and a critical analysis of the STEM 'pipeline'. Specifically, the fact that many students report early interest in STEM but drop out as undergraduate students, graduate students, or early career professionals indicates that this is more than an issue of early recruitment, but a more serious flaw in the 'pipeline' [9]–[11].

As a result, many methods attempting to engage and retain a wider array of students have been suggested and tested [12]–[14]. Key among them is the idea of 'identity', or the extent to which students identify with their field and feel that they belong in it [15], [16]. Strong field identities have been linked to persistence and success in STEM [17], [18], and STEM interest is often linked to the potential of a STEM identity – that is, students are less likely to report an interest in STEM if they feel they will not be able to build an identity within it [19]. For example, several studies have indicated that negative stereotypes about STEM professionals, such as the idea that they are asocial or interpersonally incompetent, have been shown to decrease interest in STEM, particularly among women [20], and that the reverse – positive stereotypes and increased interest – is also true [21]. Those with stronger STEM identities, and who do not perceive STEM to be exclusive in the type of people admitted (e.g., low STEM gender stereotypes), find more success as students and as professionals [22].

In response to these findings, interventions developed to challenge students' stereotypes of STEM professionals – with a goal of strengthening interest and buffering against attrition – are becoming more frequent. Some have focused on the type of people who are interested and successful in STEM: since biased representations of STEM professionals generally portray them as white and male, educators have attempted to change these portrayals by spotlighting the diversity that already exists in the field [23], [24]. Other stereotypes pigeonhole STEM careers as those that focus excessively on laboratory work and mechanical tinkering, overlooking both the social needs that drive technological innovation as well as the social contexts in which they occur. To counter this, some interventions focus on the communal and social qualities of STEM work, drawing in students previously left cold by stereotypes of asocial loners [25], [26].

Stereotypes of Scientists (and Engineers)

To help improve and clarify assessment of these interventions, as well as create a method of measuring students' scientist identities, the Stereotypes of Scientists Scale (4S) was developed [27]. The 4S uses the idea of 'fit' to assess science identity – it assesses students' beliefs about scientists, as well as their beliefs about themselves, to measure the overlap or potential fit they experience with STEM roles as defined by the participant. For instance, a student who perceives scientists as highly intelligent but uninterested in socializing and working with others, while also perceiving themselves as intelligent and interested in working to improve others' lives, would be considered to have low fit. However, a student who views themselves as able to succeed academically and who prefers working with objects rather than people, and who views science as the work of tinkering with complex technology alone in a laboratory, would be considered to have high fit, and would likely see a science career as very possible.

In support of these conclusions, research indicates that many academically successful students with a prosocial focus often chose to major in the social sciences or human health fields – 'soft science' or 'applied fields' which are often considered 'less STEM' than others like chemistry, engineering, or programming [28], [29]. Often these students began in a traditional STEM major, and were considered to 'drop out', or to be part of the 'leaky pipeline', when they chose to become nurses, medical doctors, or social scientists – fields which are more applied, more communal, and much more diverse [30].

Differences Between STEM Fields

At this point, it is important to step back and note that – although they're often presented as a single entity – there are differences between science, technology, engineering, and math fields. The tendency to overlook these differences is especially problematic for researchers working in engineering education, as much of the literature regarding STEM identity, belonging, and retention draws from studies that assume one STEM field is like any other [9], [31], [32].

However, there are multiple indications that this is not the case. First, there are different patterns in representation and diversity depending on one's specific field: engineering and computer science fields, for instance, are largely made up of White men (50% and 47%), Asian men (8% and 7%), and White women (11% and 8%). On the other hand, fields such as the biological sciences or mathematics and statistics show a more diverse pattern of enrollment – (24% and 34%) White men, (33% and 25%) White women, (6% and 6%) Asian men, (8% and 4%) Asian women, and (3% and 3%) other men of color and (7% and 3%) other women of color (NSF & NCSES, 2017). These differences in representation are echoed by students' and professionals' perceptions of their field as more or less diverse and inclusive [22], and these perceptions of climate and equality go on to affect persistence and representation among minority populations [33], [34].

Second, students perceive majors to require clear differences in intellectual rigor, which influences interest and retention. For instance, math, physics, and computer science are often characterized by strict ability beliefs, or the idea that one must be innately intelligent or 'brilliant' in order to succeed within them. On the opposite end of the spectrum are more applied fields such as psychology, molecular biology, and earth science. Fields with a stronger ability beliefs also end up less diverse – they have fewer female degree earners and fewer degree earners from marginalized racial backgrounds [35].

Responding to the crises of recruitment, retention, and representation in STEM requires tools sensitive to the differences between STEM fields, but flexible enough to capture the similarities and patterns across STEM. The 4S, introduced above, is a potential solution to this problem, although it faces some challenges. Specifically, the scale was crafted using the language of 'science' and 'scientists', although it was tested with students from approximately 60 majors, including education, psychology, aerospace engineering, and biology [36]. Attempts to use the 4S to assess identity in 'non-science' fields – such as technology and engineering – may thus be foiled by the scale's vocabulary and development. Comparing the scale's performance across majors is one way to test how well it functions across STEM populations, and that is the solution proposed in this paper.

The Current Study

The current study seeks to explore, using existing data, whether the 4S and assorted measures work well with non-science STEM populations. The initial data collection was for survey development and focused specifically on science identity and perceptions of science, rather than STEM fields broadly. Although students from many majors were surveyed, the focus on items was clearly on science rather than technology, engineering, or math. In addition, the measure has been used largely with science populations (e.g., introductory biology students, see Perkins, Wyer, & Schinske (2018)), but the possibility of expanding the survey to work with other populations, such as engineering, has also been raised. However, this would require a new span of survey development and testing. Before proceeding with new data collection, we sought to explore how well the measures worked in our initial study sample, particularly for students who weren't 'science' students, as it was possible the measures had no relevance for them.

Although this data is several years old and skewed towards science fields and science identity, we believe that evaluating the predictive validity of the measures across groups provides guidance before moving forward with a new sample and revised items. Additionally, conducting these analyses with the early sample will allow for closer comparison when new data is collected, thus providing a more refined analysis of how the measure's wording impacts its usefulness as a psychometric tool. To this end, the current study re-analyzes the previously collected data and explores how students' gender, major, and perceptions of equality influence their career intentions. The goal of this analysis is to evaluate the scale's baseline functioning within engineering populations and to further explore how students' identities and majors interact to affect students' STEM career interest.

Method

Participants

Responses were collected from 1,654 participants gathered across a national sample of STEM majors across 38 classrooms [38]. The current study limited the participant pool to those enrolled in STEM majors (more information on how this was determined is provided below), resulting in a sample of 1,071 participants. The sample for this study was 48% male and marginally diverse (68% White, 16% Asian, 7% Black, and 4% Hispanic/Latino). Over sixty concentrations were provided as students' majors, with over 300 students selecting 'other not listed' and writing in a response. These responses were evaluated, and if they fit with a previously listed major or into the STEM coding scheme outlined below, were recoded.

Measures

Gender. Students were asked to report their gender in a single item at the end of the survey. Only two response options were provided, 'male' and 'female'.

Major. Because of the variety of majors provided, the data did not support analyses by individual major and were grouped according to 'field' (see Table A1 for full list and coding). This resulted in programs such as biology, biochemistry, and statistics being coded as Science/Math, and programs such as biomedical engineering, chemical engineering, and computer science being coded as Engineering/Technology. This was done following conventions regarding content similarity, demographic patterns of gender and representation, and established grouping procedures. For example, many universities group computer science programs with engineering programs in their Colleges of Engineering, and group statistics and mathematics courses into their Colleges of Science (NCSU, 2018). For majors in which these distinctions were not clear, researchers used the definition proposed by Petroski (2010), in which programs that focus on understanding are categorized as 'science', and those that focus on applying science to technological innovation as 'engineering'. Although dividing and testing our sample in this manner will not produce results as accurate as those that might be obtained when using revised items, this division provides us the chance to assess the measure's general functioning across groups before collecting new data.

Stereotypes of Scientists Scale (4S). The 4S consists of 22 items that query students about their perceptions of scientists and themselves (see Table A2 for full list of items). This scale has been tested and developed with undergraduates, and has been shown to predict students' science career interest [36], [41] and to be psychometrically valid for men and women [27]. This is in comparison to other measures which focus primarily on assessing women's fit within science fields, thus overlooking the ways in which men may experience poor fit (e.g., Settles (2004)). To calculate fit, students' responses to parallel items are coded; items in which students' responses were the same (e.g., they rate themselves and scientists as equally logical) were coded as 1, and items in which responses differed were coded as 0. Items were averaged, creating a fit score that ranged between 0 and 1, with lower scores indicating poorer fit.

Critical Vision Scale (CVS). The full Critical Vision Scale (referred to in the literature as the Social Equality Perceptions in Science Scale) consists of 14 items that ask students to rate their agreement to statements about equality in science (see Table A3 for full list of items) [38]. Previous exploratory factor analysis indicated a two-factor solution, in which items that ask about how equality in science *should be* loaded separately from those that ask about how equality *is*. As the focus on this analysis was on students' perceptions of realized equality in science, only the seven items loading in the second factor were used in this analysis. Responses were averaged, with higher scores indicating more perceived equality.

Career Intentions Scale (CIS). The Career Intentions Scale consists of 12 items that ask students how likely they are to attain various science milestones (see Table A4 for full list of items) [38]. Items were averaged, with a higher score indicating that the participant reported more interest in science training and/or careers.

Analysis

Before conducting the analyses outlined below, the data was tested to confirm it fit the expectations of the tests. Bivariate correlations were run for the variables of interest (fit score, CVS score, CIS score, gender, and major), and Z-scores were calculated to test for outliers. The composite variables tested for normality by assessing skewness, kurtosis, residuals, homoscedasticity, and linearity. An ANOVA was run to test for significant differences in CVS score according to major, with gender run as a covariate. This was done to test the effect of major on CVS independent of the fit-CVS relationship which will be tested in the analyses below.

All mediation, moderation, and conditional process analyses (CPA) were conducted in SPSS using the PROCESS macro [43], [44]. In preparation for the full CPA (also referred to as moderated mediation), three preliminary analyses were conducted. Major and gender were tested as potential moderators on the fit-CIS relationship, to examine their influence on the model independent of CVS, and to further evaluate the 4S with use in the broader STEM population. Additionally, a mediation analysis was run for CVS on the fit-CIS relationship – previous analyses had indicated that CVS, CIS, and fit were all significantly correlated, and so this analysis sought to determine how much of the effect of fit on CIS could be accounted for by CVS.

The final model (see Figure A1) was run to test the full effect of critical vision on students' fit scores and their career intentions, as potentially moderated by major and gender. It was theorized that major would moderate the relationship between fit and CVS (i.e., that Engineering/Technology students would have a stronger relationship between fit score and critical vision, while Science/Math students' fit scores would be less related to their critical vision, due to the greater perceived equality in those fields), and that gender would moderate the relationship between CVS and CIS (women's career intentions would be more related to their critical vision, while men's career intentions would be the same regardless of perceived equality in their fields). If supported, these hypotheses would demonstrate that the measure in its current state – with a large focus on scientists and science rather than STEM overall – still functioned as a rough measure of students' identities, perceptions, and aspirations in their fields.

Results

Any participant whose score was more than three standard deviations from the mean was considered an outlier. Analysis of the variables of interest revealed twenty-one participants with CVS, CIS, or fit scores that matched this criteria; these participants were dropped from the analysis (n = 1050). Skewness and kurtosis for the three composite variables (CVS, CIS, and fit scores) were within normal ranges (less than one). Analysis of the normal probability-plot indicated that the assumption of linearity was upheld, and that there were no issues with homoscedasticity.

Bivariate correlations were conducted for the variables of interest and found some small significant relationships (see Table A5). Neither major (Science/Math or Engineering/Technology) nor gender had significant relationships with fit score, and major did not predict CVS. Furthermore, a 2x1 ANOVA did not find a significant effect of major on CVS score, with Science/Math (M = 4.27, SE = .03) and Engineering/Technology (M = 4.20, SE = .06) students reporting similar CVS scores when controlling for gender.

To demonstrate that the 4S accurately predicts career interest in men and women and in Science/Math and Engineering/Technology majors, major and gender were tested as moderators of the relationship between fit and CIS. Neither gender (b = -.22, SE = .36, p = .546) nor major (b = .38, SE = .43, p = .379) were found to interact significantly with the fit-CIS relationship. Mediation analysis determined that critical vision (CVS) partially mediates the relationship between fit and career interest (CIS), but that the relationship between fit and CIS remains strong (see Figure A2). Fit was a significant predictor of CIS, b = .89, SE = .18, p < .0001, and of CVS, b = .59, SE = .17, p = .0007, and remained significant (although lessened) when accounting for CVS, b = .85, SE = .18, p < .0001. A small amount of the variance in CIS was accounted for by the predictors (R^2 = .03). Bootstrap estimation (with 5000 samples) was used to test the indirect effect [43], and it was found to be significant, b = .05, SE = .02, 95% CI = .005, .093. In conclusion, an increase in fit predicted a minor increase in CIS, as mediated by CVS.

The above analyses indicated the predicted relationship between fit, CVS, and CIS existed, and that major and gender alone did not predict differences in the fit-CIS relationship. However, the effects of major and gender on the fit, CVS, and CIS relationship were still unknown. Using CPA, major and gender were added as moderators to the previous mediation model (see Figure A1). Major was found to significantly predict critical vision, b = -.46, SE = .19, p < .013, with Engineering/Technology majors reporting lower CVS; gender was also found to predict STEM career interest, b = .79, SE = .28, p < .0044, with men reporting higher CIS (see Figure A3).

Furthermore, as predicted, major and gender were found to moderate the fit-CVS-CIS relationship (see Figure A4). Major interacted with the relationship between fit and critical vision, b = 1.14, SE = .41, p < .0058. Decomposition of the interaction indicates that there is a positive relationship between fit and CVS for Engineering/Technology students, b = 1.47, SE = .36, p = .0001, and that Science/Math students' fit and CVS scores were unrelated, b = .33, SE = .19, p < .089 (see Figure 5). Gender also interacted with the relationship between critical vision and career interest, b = -.14, SE = .06, p < .027. As predicted, there was a significant effect of gender on the CVS-CIS relationship, b = .17, SE = .05, p < .0003, and no effect of critical vision on men's STEM career interest, b = .03, SE = .04, p = .426 (see Figure A6). Bootstrap estimation (with 10,000 samples) indicated that there was a conditional moderated mediation effect, or that the indirect effect of major on the fit-CVS relationship interacts with the CVS-CIS relationship for women, b = .20, SE = .10, 95% CI = .035, .433, but not for men, b = .04, SE = .05, 95% CI -.049, .158.

Discussion

In summary, the primary goal of this paper was to compare the use of 4S across majors by assessing how well it predicted science career interest. In addition, this paper also sought to explore how critical vision impacts science career interest and how it interacts with students' characteristics (specifically major and gender). The predictive validity of the fit-CIS relationship was not moderated by major, indicating that it functions similarly as a predictive tool for both Science/Math and Engineering/Technology students. However, critical vision was found to partially mediate the fit-CIS relationship, indicating that some of the differences in STEM career interest predicted by fit scores can be explained by students' perceptions of equality in their field – a mediation effect found to be moderated in turn by major and gender.

This does not impact the ability of the 4S to predict STEM career interest but indicates that the influence of the mediator (critical vision) functions differently depending on student characteristics. Conditional process analysis indicated that the positive relationship between fit and critical vision existed only for Engineering/Technology students, and that the positive relationship between critical vision and career interest existed only for women. As a result, we can conclude that the mediation effect of critical vision is powered by women in Engineering and Technology majors, but that critical vision is not a mediator for Science/Math students and men across majors. However, it should be explicitly noted that all effect sizes are small, particularly given the study's large sample size.

The moderated mediation of critical vision on the fit-CIS relationship also highlights the importance of critical vision. A significant component of the fit-CIS relationship is mediated, or can be explained by, students' perceptions of equality in their field. This reinforces existing messages about the importance of equality in recruiting and retaining students, but also indicates that interventions which convey messages of belonging and equality may be another way to promote STEM career interest [12], [45]. This includes not only increasing and defending policies designed to create diversity, but also advertising the diversity that already exists within the field and practicing other forms of inclusiveness [24], [35]. However, as with the 4S and the CIS, the critical vision scale is also science oriented, and thus administering a modified version of the scale would likely find much stronger results.

Limitations

These results confirm that the 4S does not function poorly for Engineering/Technology, but the deflated effect sizes indicate that a more refined measure of engineering identity and engineering career intentions are still needed. The age of the data (collected in 2010) and the focus on science students are also drawbacks of using the current data in this analysis. As we proceed with scale development and refinement, we will ensure a more balanced population of students, as well as investigating the ways that stereotypes and preconceptions of STEM have changed over the years. Once again, the goal here was to test the survey across the two rough populations of STEM students (science/math and engineering/technology) and develop hypothesis regarding the importance of gender, major, and critical vision in the fit/CIS relationship; we believe that we have done this, despite the limitations of our current dataset, but look forward to conducting a fuller analysis with more refined data in the future.

Conclusion

Overall, these findings reinforce the need for specialized measures for use with different STEM populations, but also support the call for decreased stereotypes, increased awareness and acceptance of diversity, and to vigilance surrounding about micro-aggressions and subtle messages of inequality. For instance, the ‘I Look Like an Engineer’ Twitter campaign combats stereotypes by acknowledging them as falsehoods; although limited, there is already diversity in STEM, and patterns of student enrollment indicate that this diversity will continue to increase [46]. As indicated here, further refining the 4S and other measures could lead to the use of a tool that better assesses ‘fit’ within Science/Math and Engineering/Technology populations, as well as how students’ perceptions of equality in their field shift as their exposure to diversity increases. This will allow interventionists and engineering educators to identify not just for whom, but also how and why their efforts are successful, and the results can be used to identifying areas of potential improvement and psychological mechanisms of interest.

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Appendix

Table 1

Majors Reported by Participants and Arranged by Assigned Code

Code	Major	Count
Science/Math	Total	805
	Agricultural	29
	Agroecology	1
	Animal Sciences	73
	Biochemistry	77
	Biochemistry and Molecular Biology	1
	Biological Sciences	3
	Biology	336
	Bioprocessing	4
	Botany	20
	Chemistry	55
	Food Science	29
	Horticultural Science	2
	Mathematics	32
	Meteorology	21
	Microbiology	14
	Neuroscience	2
	Other STEM	27
	Physics	16
	Statistics	6
	Zoology	57
Engineering/Technology	Total	266
	Aerospace Engineering	18
	Agricultural and Biological Engineering	1
	Agricultural and Environmental Technology	1
	Biological Engineering	7
	Biomedical Engineering	79
	Chemical Engineering	42
	Civil Engineering	18
	Computer Engineering	3
	Computer Science	27
	Electrical Engineering	10
	Environmental Engineering	7
	Environmental Systems Engineering	3
	Industrial Engineering	4
	Materials Engineering	4
	Mechanical Engineering	25
	Nuclear Engineering	2

	Other Engineering	10
	Systems Engineering	3
	Textile Engineering	2
Non-STEM*	Total	440
	Business and Marketing Education	70
	Elementary Education	15
	English	12
	General Studies Education	1
	Math Education	13
	Middle Grades Education	4
	Natural Resources	22
	Other Not Listed	230
	Philosophy	5
	Science Education	11
	Technology Education	1
	Undecided Major	56
Social Science*	Total	143
	Accounting	5
	Anthropology	15
	Cognitive Science	4
	Economics	11
	History	7
	Political Science	23
	Psychology	67
	Social Work	1
	Sociology	10

* These categories were not included in this paper's analyses

Table A2

Stereotypes of Scientists Scale (4S)

Professional Competencies
Know a lot about the latest discoveries
The ones who know how equipment works
Careful with expensive instruments
Competitive
Independent
Work oriented
Technically competent
Competent
Self-confident
Highly focused
Able to learn to use new equipment quickly
Especially intelligent
Logical
Interpersonal Competencies
Have fun with colleagues at work
Maintain friendships with colleagues in other departments
Do not have a lot of friends *
Out of touch with what is happening in the world *
Have happy marriages
Cooperative
Family oriented
Insecure *
Collaborative

Note: Item stems read, "When I think about myself, I think I am someone who…." and "When I think about scientists I think they are…."

* indicates reverse-coded item

Table A3

Critical Vision Scale (CVS)

Ideal State
Women and men SHOULD have equally successful science careers.
Women and men SHOULD receive equal schooling opportunities in science.
Women and men SHOULD receive equal employment opportunities in science.
People of all ethnic groups SHOULD have equally successful science careers.
People of all ethnic groups SHOULD receive equal schooling opportunities in science.
People of all ethnic groups SHOULD receive equal employment opportunities in science.
In my ethnic group, men and women SHOULD have the same educational and employment opportunities in science.
Actual State
Women and men DO have equally successful science careers.
Women and men DO receive equal schooling opportunities in science.
Women and men DO receive equal employment opportunities in science.
People of all ethnic groups DO have equally successful science careers.
People of all ethnic groups DO receive equal schooling opportunities in science.
People of all ethnic groups DO receive equal employment opportunities in science.
In my ethnic group, men and women DO have the same educational and employment opportunities in science.

Note: Participants were asked to rate how much they agreed with each statement. Only items from the second factor (Actual State) were used in this paper's analyses.

Table A4

Career Intentions Scale (CIS)

Scale Items
Get college training in science
Get experience working as a scientist
Be a successful scientist
Get an advanced degree in science
Become a scientist
Have the ability to become a scientist
Take advanced courses in science
Complete your degree in science
Do advanced research in science
Apply to graduate programs in science
Have a lifelong career in science
Have a very successful career in science

Note: Participants were asked to rate how likely it is they will take the following career step.

Table A5

Bivariate Correlations among Variables of Interest

Variable	1	2	3	4
1. Critical Vision Scale (CVS)	--			
2. Fit Score (4S)	0.108**	--		
3. Career Interest Score (CIS)	0.073*		--	
4. Gender	-0.168**	-0.016**		--
5. Major	0.009	-0.011	-0.082**	-0.234**

* $p < .05$

** $p < .01$

Figure A1

Full Model of Conditional Process Analysis (CPA)

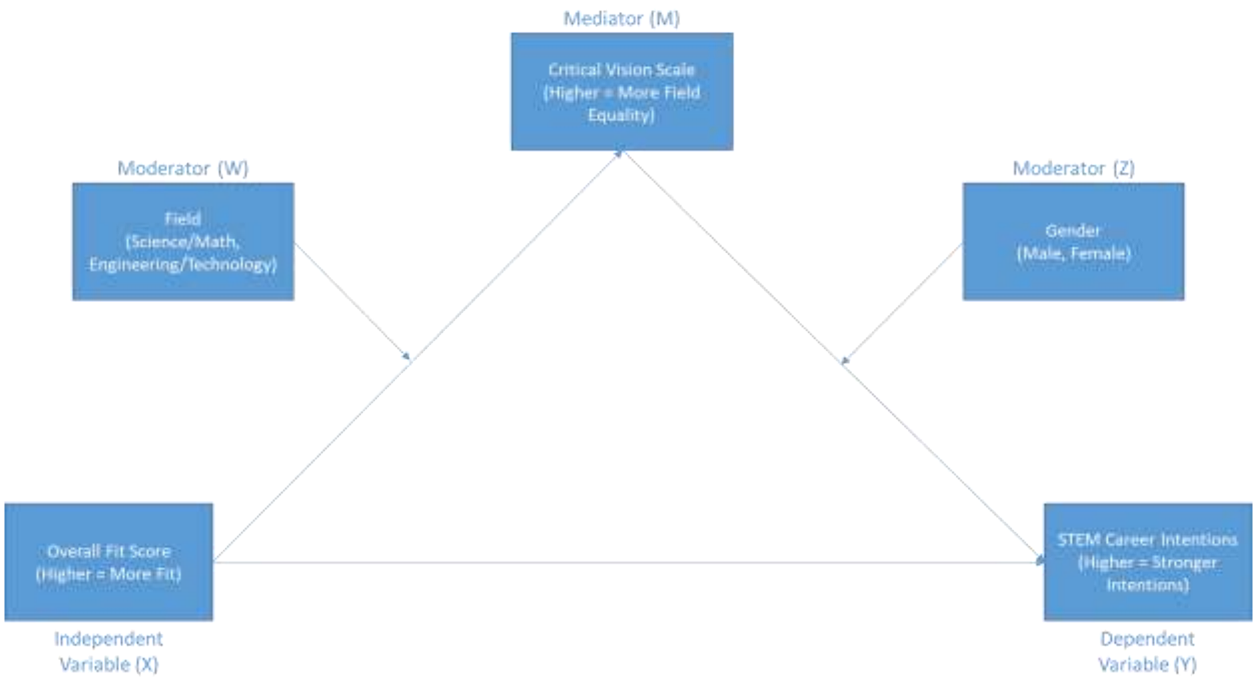

Figure A2
Preliminary Mediation Model

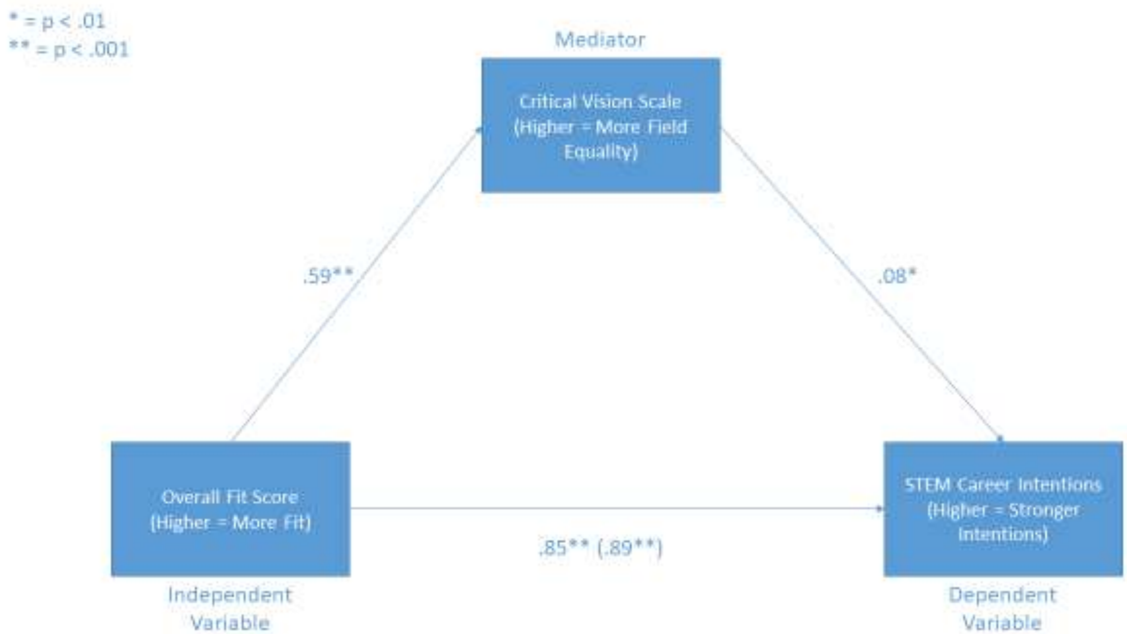

Figure A3
Preliminary Moderation Model

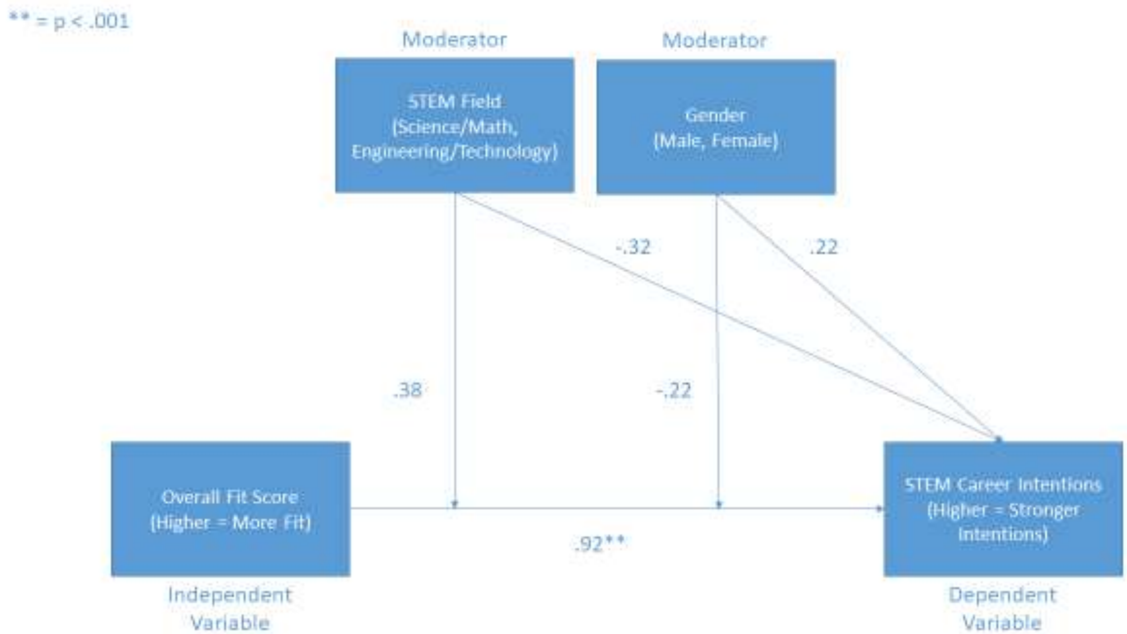

Figure A4
Final CPA Model (Moderated Mediation)

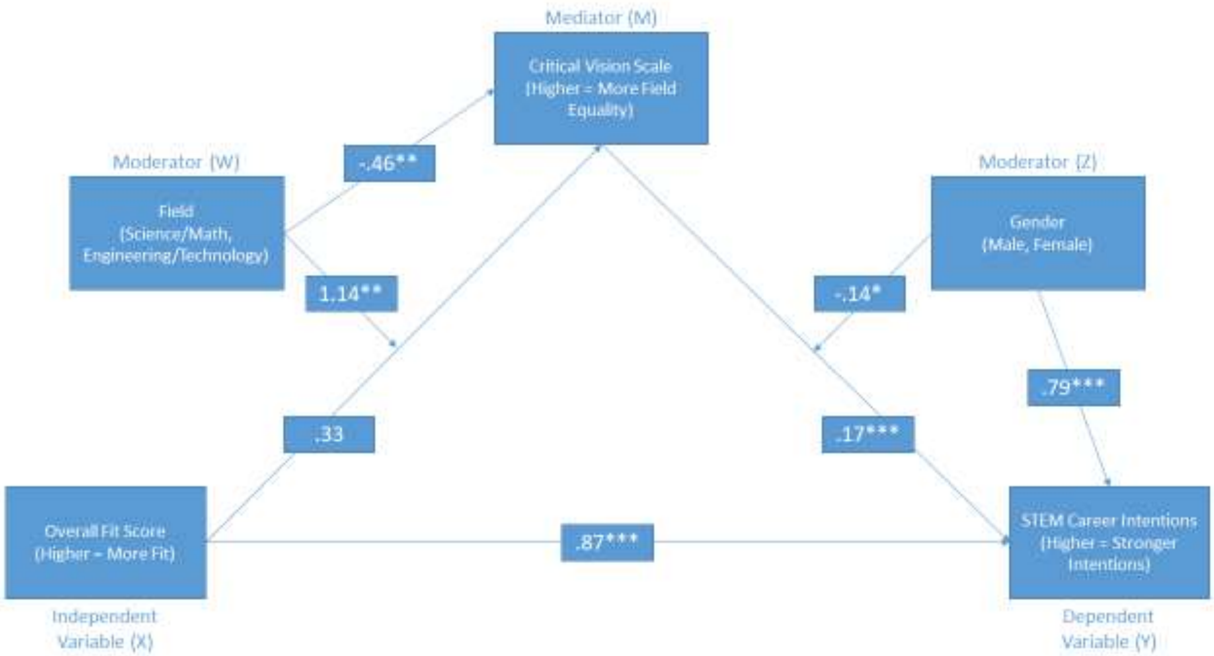

Figure A5
Effect of Major on Relationship Between Fit Score and Critical Vision Score

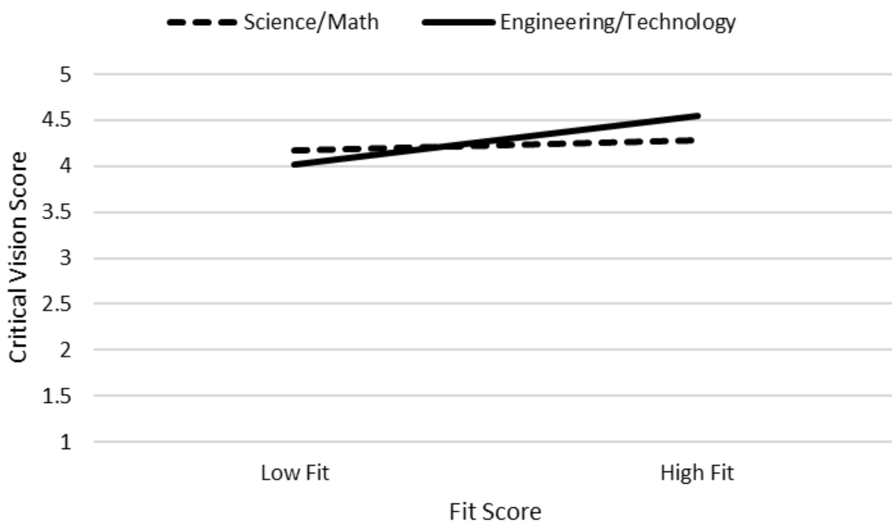

Figure A6
Effect of Gender on Relationship Between Critical Vision Score and STEM Career Intentions