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Implicit and Explicit Balanced Identity Scores Vary as a Function of Gender and STEM Major

Rachelle Pedersen, Texas A&M University

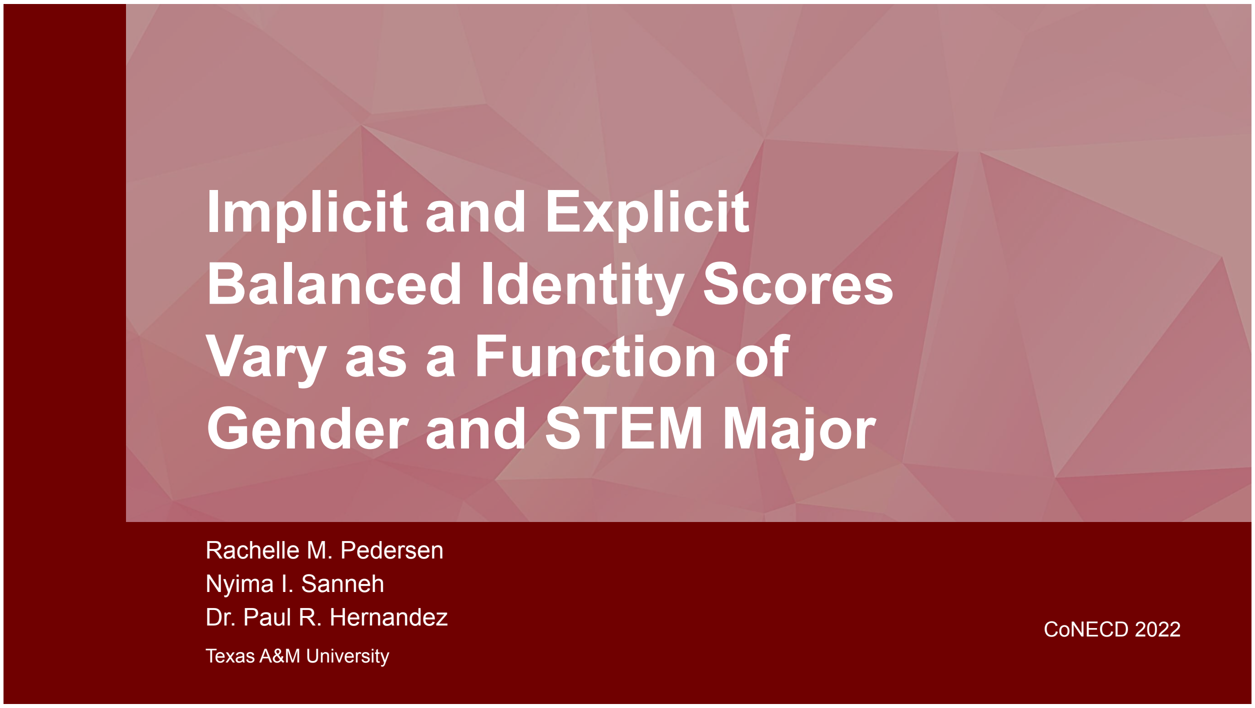
Rachelle Pedersen is a first-year Ph.D. student pursuing a degree in Curriculum and Instruction with an emphasis in Engineering Education at Texas A&M University. She holds a Master's of Science in Curriculum & Instruction from Texas A&M and a Bachelor's of Science in Engineering Science (Technology Education) from Colorado State University. She previously taught for 5 years in Connecticut at a high school teaching technology education. Rachelle's research interests center around broadening participation in STEM (specifically Engineering) education and the role of identity development and social influencers on belonging and persistence in the field.

Nyima Sanneh, Motivation and Learning Lab

Nyima Sanneh is a 2nd year student at Texas A&M University pursuing a Bachelors of Science in Aerospace Engineering. Nyima's research interests have been related to understanding the gender and racial disparities in STEM and finding ways to correct these gaps. As a second year undergraduate researcher for the Motivation and Learning Lab, Nyima has been able to aid in this kind of research, presenting during Student Research Week.

Dr. Paul R Hernandez, Texas A&M University

I earned a Ph.D. in Educational Psychology from the University of Connecticut in 2011. I'm currently an Associate Professor in the Department of Teaching, Learning and Culture (Joint appointment in Educational Psychology) at Texas A&M University. I teach graduate courses in measurement, research design, and statistics. My research focuses on the contextual factors, developmental relationships, and motivational processes that support and broaden participation in Science, Technology, Engineering, and Mathematics (STEM) careers – particularly for students from groups historically underrepresented in STEM.



My name is Rachelle Pedersen and I am a Ph.D. student in Curriculum & Instruction at Texas A&M University. With me is Nyima Sanneh, an undergraduate researcher who has been working on this project with us alongside Dr. Paul Hernandez. Our project is titled “Implicit and Explicit Balanced Identity Scores Vary as a Function of Gender and STEM Major.”

Outline

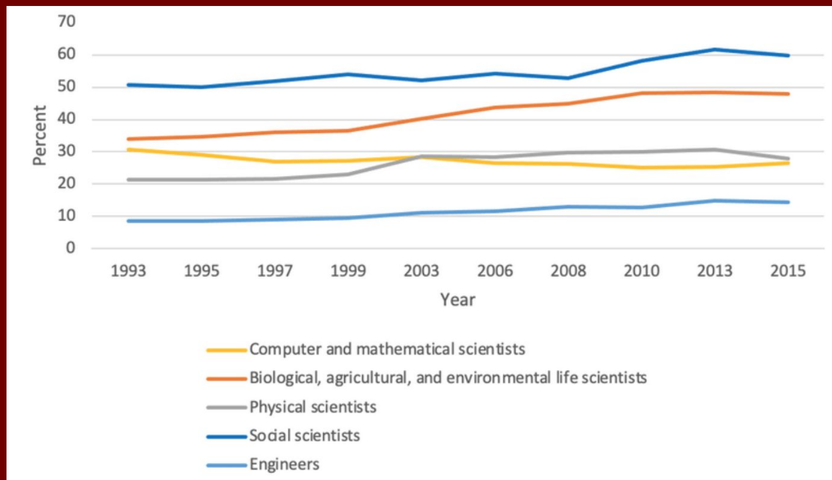
- Context of the Study
- Balanced Identity Theory
- Current Study
- Preliminary Analyses
- Results
- Discussion
- Limitations
- Future Research

Here is a brief outline of what we will be going over during our presentation today.

Introduction

28%

of the STEM workforce are women



NGC, National Girls Collaborative Statistics. (2020). Retrieved from https://ngcproject.org/statistics

The graph shows the percentage of women in different fields of STEM from 1993 to 2015. Social sciences and Biological and Life Science have reached above or near 50% representation of men and women, while Compuer Science and Engineering are around or less than 20% women.

Regardless of pre-collegiate academic abilities, women are underrepresented in many fields of science, technology, engineering, and mathematics. According to NGC 2020, “Women make up half of the total U.S. college-educated workforce, but only 28% of the science and engineering workforce.” Upon further analysis, we find that these numbers are significantly lower in engineering and computer science fields. The image on the right shows how several fields within STEM have made great progress in closer the gender gap, such as Biological and Life sciences, while others like computer science and engineering are still struggling to have equal representation. Exposure to persistent gender stereotypes, often reinforced by numerical dominance, can contribute to a lower sense of belonging for women in STEM.

Introduction

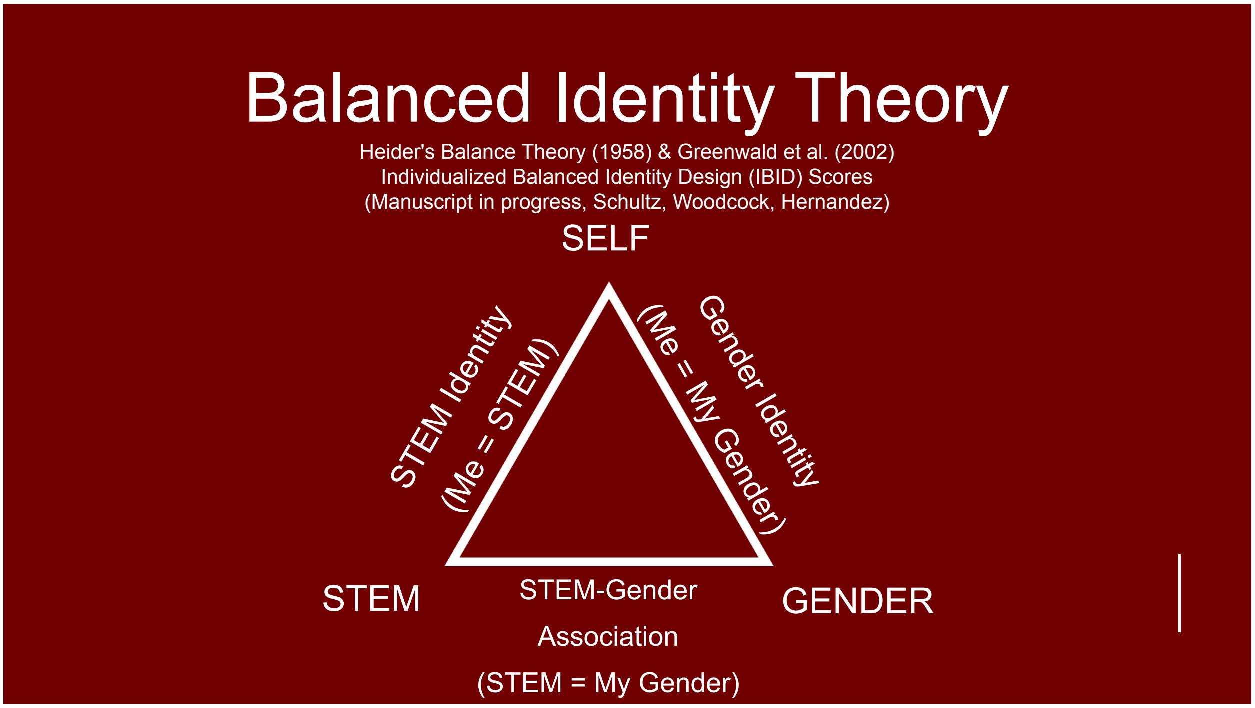
Dasgupta & Stout, 2014

This image (from The New Yorker) has a women in the center of a crowd of all men. The men are in black and white and the woman is in color and looks distraught.

https://bit.ly/2V5MiSY

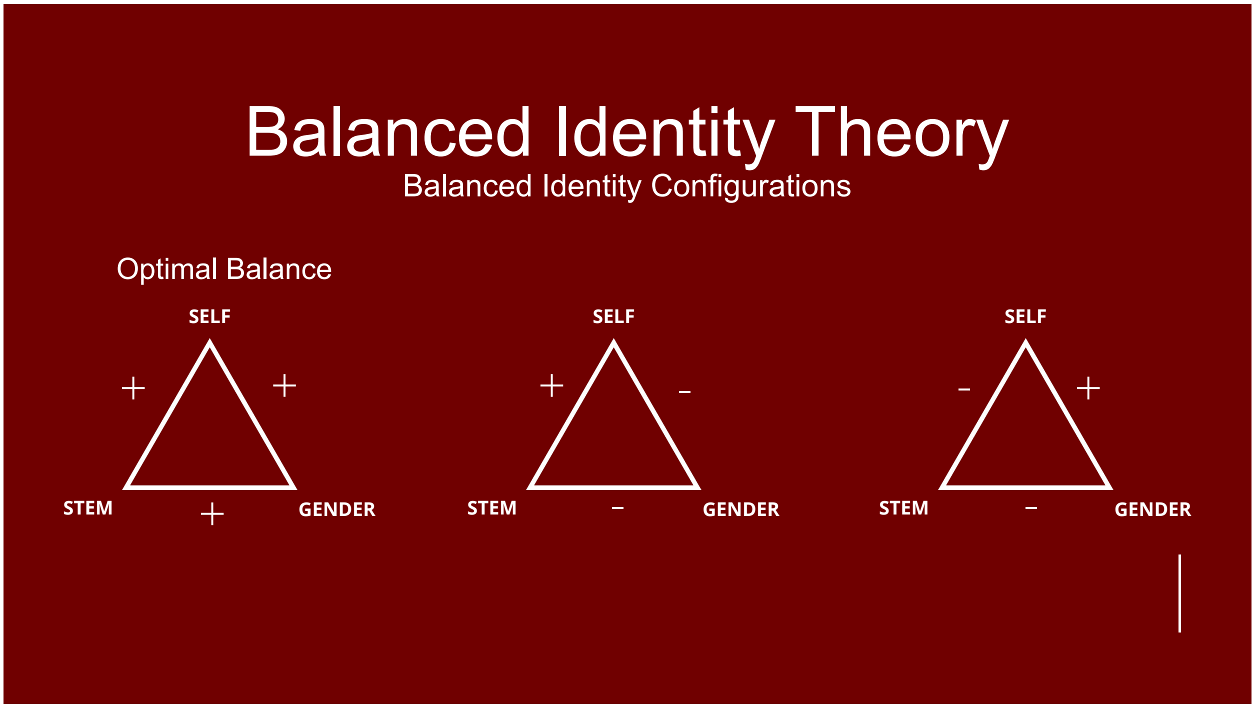
According to Dasgupta and Stout in 2014, “In childhood and adolescence, masculine stereotypes about STEM, parents’ expectations of daughters, peer norms, and lack of fit with personal goals make girls move away from STEM fields. In emerging adulthood, feeling like a misfit in STEM classes, being vastly outnumbered by male peers, and lacking female role models make women avoid STEM majors or leave prematurely.”

Studies have shown that personal-professional identity development supports persistence intentions and belonging for women in STEM fields. But while STEM students are developing their STEM identities, or feelings of belonging in their STEM domain, they may also be holding gender-stereotypic associations of who actually belongs in their field. This tension of holding various associations or identities is the crux of the current study, with hopes of utilizing the methods performed to eventually determine the predictive association of balancing personal-professional identities with academic outcomes and successes.

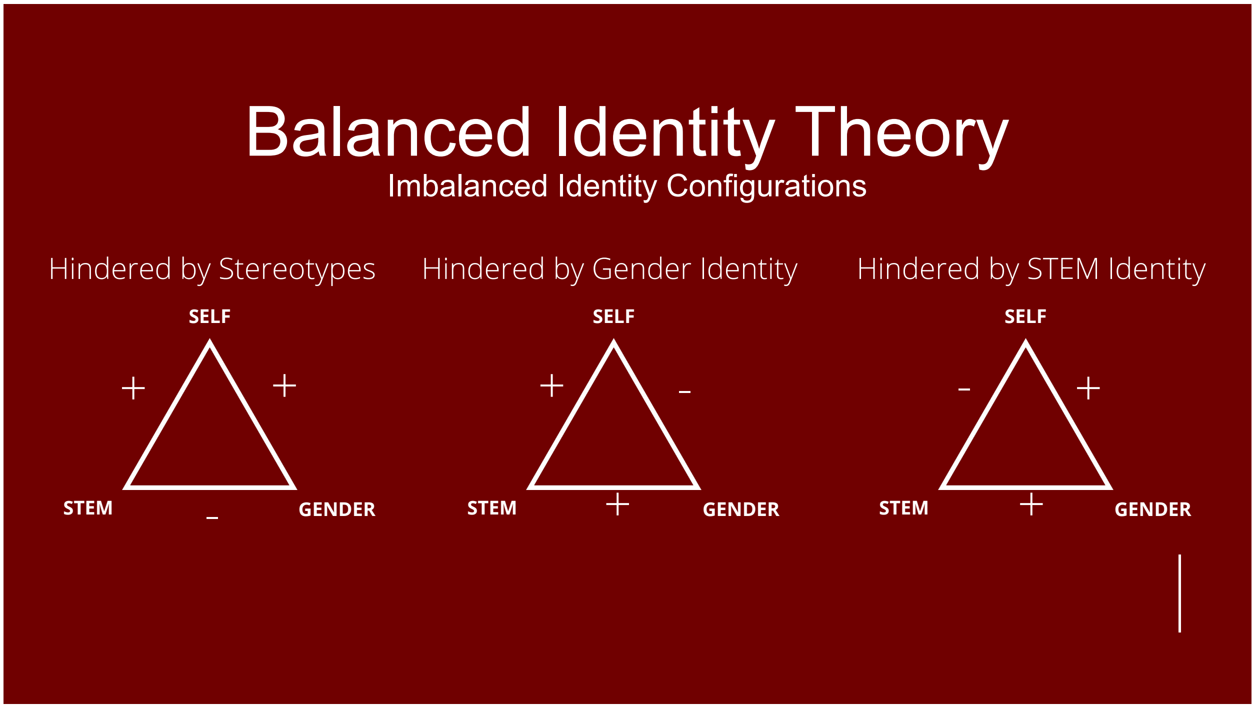


Balanced identity theory developed by Greenwald and colleagues suggests that individuals who achieve balance across central personal-professional identities will be more likely to persist in their academic and career pursuits. This study utilizes a novel methodology of individual Balanced Identity Design, which can be used to quantify the extent to which these identities are in balance or in conflict.

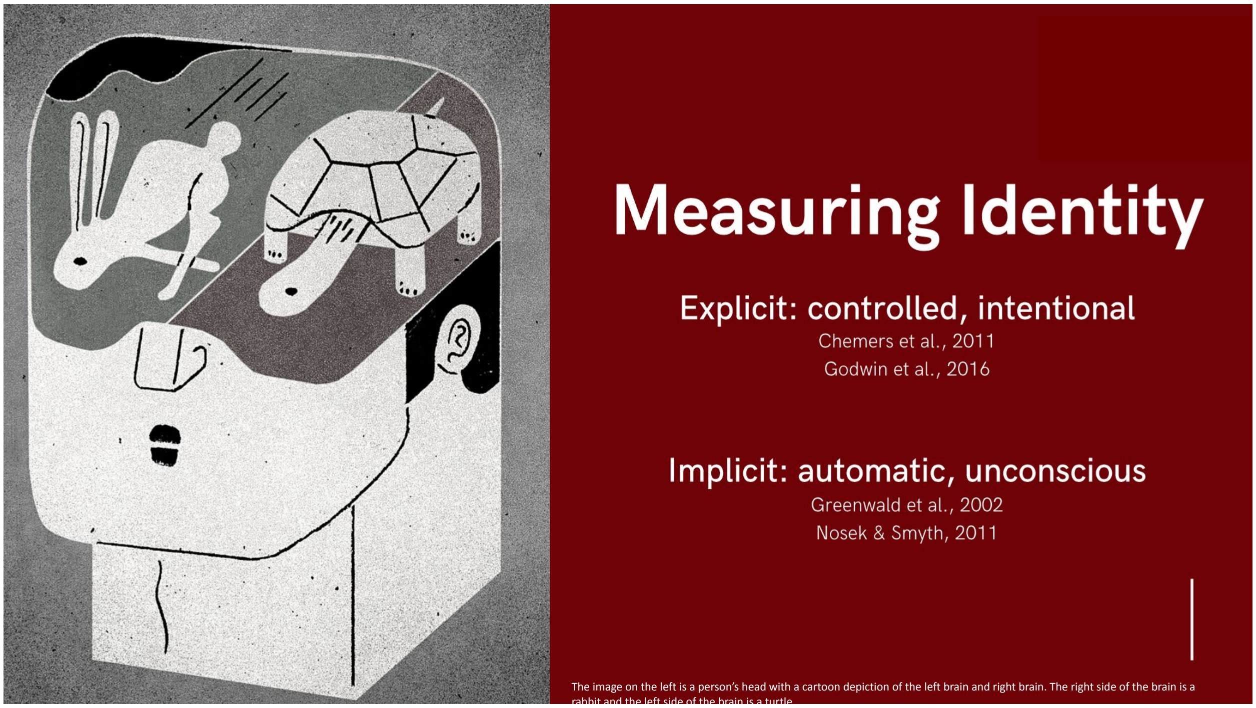
The triangle shown in the figure represents the potential tension that could exist between personal and professional identity associations. At each of the corners, we have association with self, gender, and STEM domain. So on one side, we have STEM identity (Me = STEM), on another Gender Identity (Me = My Gender), and the third being the STEM-Gender Association (STEM = My Gender). Building on Heider’s Balance Theory and Greenwald and colleagues, this triangle represents how each of these associations can be held in tension or achieve balance across all three entities.



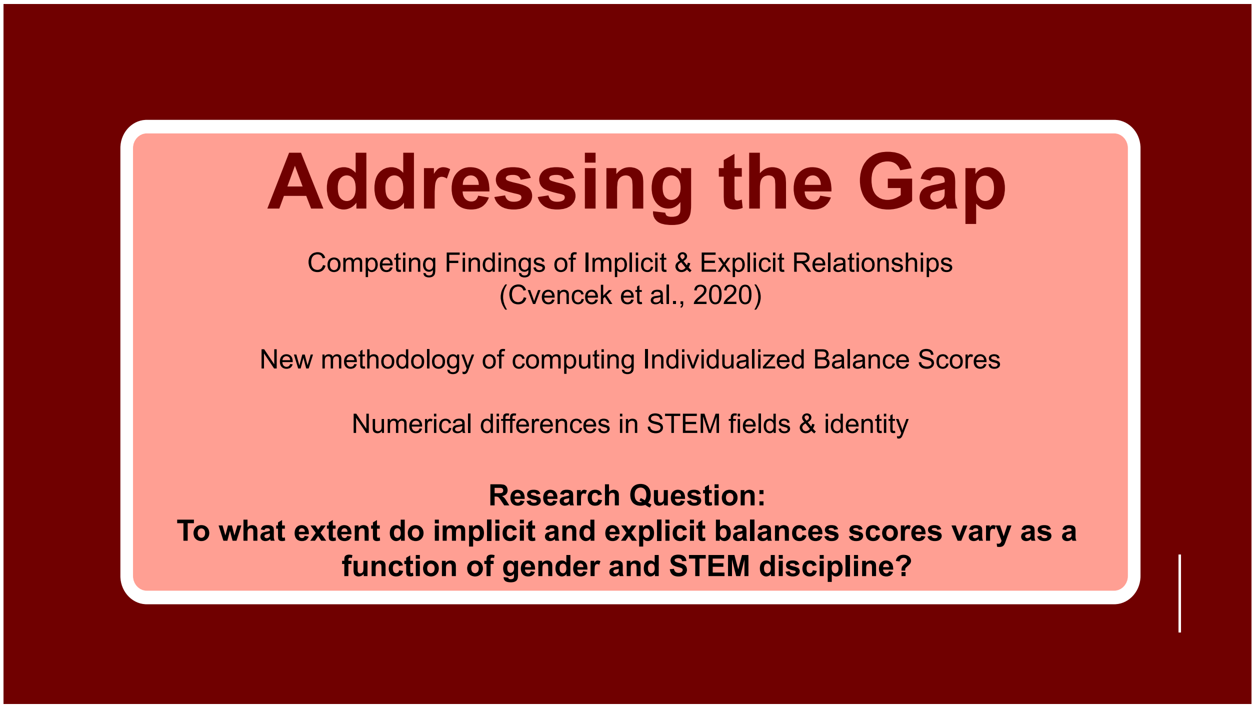
There are seven possible configurations based on Balanced Identity. Greenwald and colleagues pose that a profile is balanced when the product of all of the sides is positive. The first figure represents an optimally balanced profile, wherein the person has a positive association with Self-STEM, Self-Gender, and their Gender and STEM. The two other balanced profiles, while considered balanced from a mathematical standpoint, we would hypothesize would not be optimal for success and/or retention in STEM, as the person may find themselves either disassociating with their personal gender identity in order to match their perceptions of “who belongs” in STEM, or sacrificing their STEM identity in order to match.



These profiles represent mathematically imbalanced identity configurations. The first represents one in which the person is hindered by the STEM-gender stereotypes. Based on Balanced Theory, we would hypothesize that this person may need to make adjustments in one leg of the triangle in order to achieve balance (realistically either by positively associating STEM with their gender over time, or consequentially having a more negative view of their STEM identity, potentially leading to negative outcomes). Similar patterns exist with the other two profiles, wherein identities are held in tension until balance can be achieved in one way or the other. The 7th profile not pictured is one wherein all slides are negative, but this profile is not heavily focused on as it is not hypothesized to be probable.



It's important to define the two forms of measurement of identity that researchers often use. Most often, researchers are using explicit survey scale measures to capture the participants' attitudes or associations towards their personal-professional identities. Examples of these STEM identities are the scales developed by Chemers and colleagues for science identities, as well as Godwin and colleagues for engineering identities. With explicit scales, researchers have a way to address the participants attitudes and perceptions, yet these are also limited in the sense that participants are given time to think and respond to items; they are controlled and intentional responses. The other form of measuring identity is through the automatic, rapid-fire responses of implicit measures. An example of which, and the one used in this study, is with the Implicit Association Tests developed by Greenwald and colleagues. These measures get around the controlled response of the participant and measure the associations of terms, or implicit biases as often seen in research.



This study was originally formed from (other project) that addressed the connections between the implicit and explicit associations (an area where competing findings exist discussing the relationship between implicit and explicit measures), specifically using a new methodology of calculating balanced identity scores, for STEM students and how these associations varied by gender. Out of this study came an exploratory supplemental analysis around the idea of numerical dominance potentially impacting the implicit and explicit identities of men and women. More specifically, we looked at how there are numerical differences in the number of men and women in the various STEM fields, with fields like Biological & Life Sciences having more equal representation, numerically speaking, compared to fields like Engineering and Computer Science, and how these numerical differences might play out when it comes to the implicit and explicit identities for men and women.

Methods: Participants & Procedures

Longitudinal 5-semester study beginning in Fall 2017

N = 275, from 3 different California State University schools

51% Female,
43% White, 53% Hispanic
69% Biological Science,
20% Engineering,
11% Computer Science

Survey & Implicit Association Test (IAT) Games,
$20 incentive per survey

Current study from Wave 3

This study is a part of a 5-semester longitudinal study that began in Fall of 2017. Participants were recruited via email from 3 different California State University schools. A pre-screening survey was conducted to verify students were of junior or senior status and either white or hispanic. The analytic sample consists of 275 students, 51% of whom identify as female, 53% as Hispanic, and 43% as White. Majority of participants were in Biological Science fields. Following acceptance into the MyCollegePathways study, eligible participants completed a series of three randomly displayed, online Implicit Association Tests, and answered a series of explicit survey questions. Participants were given $20 incentives per survey prior to completion each semester. The current analytic sample is from Wave 3 of the study.

Measures

EXPLICIT SCALES

STEM Identity (Chemers et al., 2011)
eg. "I have a strong sense of belonging to the community of scientists"
Historical reliability (α=.89 and .90 for undergraduates and graduates)

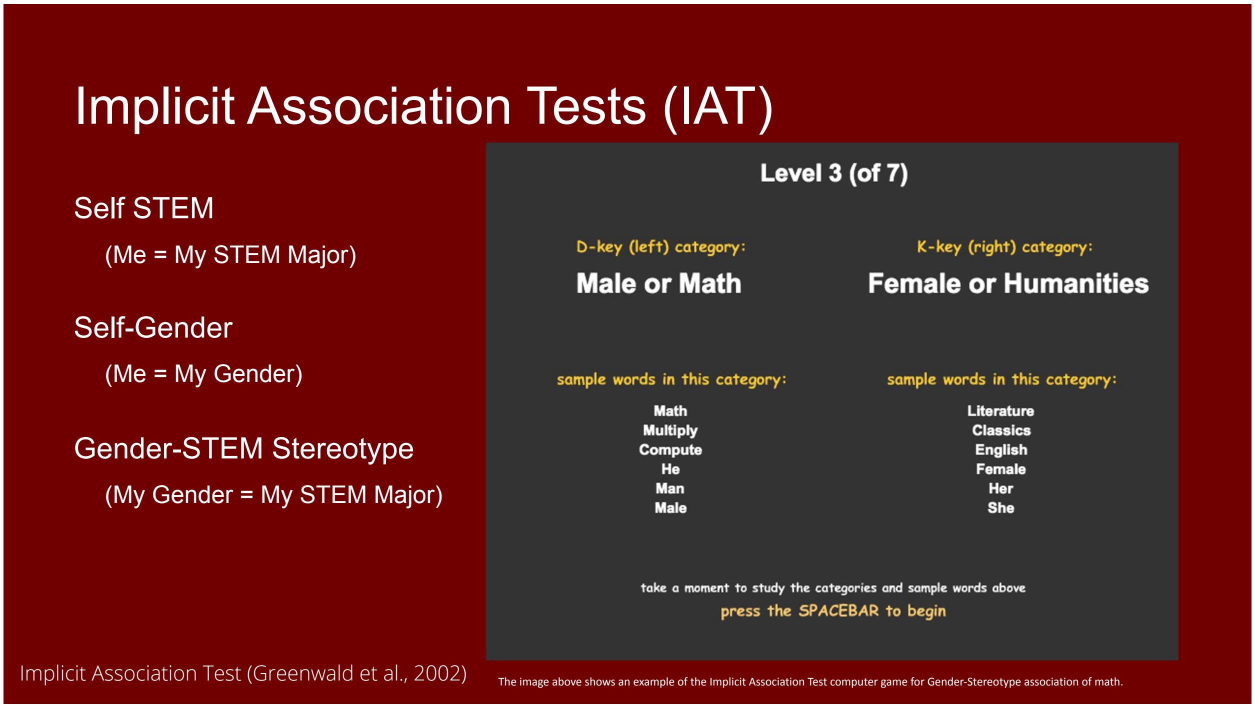
Gender Identity (Luhtanen & Crocker, 1992)
eg. "Being a man is an important reflection of who I am
Historical reliability (α= .83-.88)

Stereotype Endorsement (Schmader et al., 2004)
eg. "In general, men may be better than women at Engineering"
Historical reliability (α= .88)

To measure the extent to which participants perceived how their personal identity aligns with their selected STEM major, a shortened scale of the Science Career Identity was used. Participants answered 11 items on a scale of 1 to 5, such as “I have a strong sense of belonging to the community of scientists.” A composite score was then created by averaging the items. This scale historically has a high internal consistency for both undergradautes and graduate students.

Next, an explicit Gender Identity scale, adapted from Luhtanen and Crocker’s self-esteem subscale, was used to measure the extent to which participants identified with their gender. Each of the four items were rated on a scale of 1 to 5 and were averaged to create a composite score. The scale historically holds acceptable levels of internal consistency.

And finally for stereotype endorsement, a three-item scale was used to measure the extent to which participants endorsed various stereotypes associated with their gender and their STEM domain. Participants answered items an a scale of 1 to 5 and a composite scale was calculated by averaging the value of each of the three items. Unlike the other scales, verbiage was only worded in one way, such as “In general, men may be better than women at Engineering.” Therefore, the scores were reverse coded for women to reflect a self-gender association of the “stereotype endorsement.” The scale has a historically high internal consistency.



Implicit Association Test trios, adapted from Carpenter et al, were used to capture the strength of associations between various identities like Me=STEM and Me=My Gender, as well as stereotype endorsements like STEM=My Gender. In the IAT games, participants are shown a series of stimuli on the screen and are tasked with “sorting” the stimuli into relevant categories. The main idea of the IAT is that participants will sort the stimuli faster in a way that is consistent with their implicit association. So for someone who more strongly implicitly associates males with math, they will be able to sort the male stimuli with math category faster than when the stimuli are switched.

Scores of the reaction-based games are calculated at an individual level, wherein calculated latent response times and accuracy from a “practice” block, D1, are averaged with “test” block, D2, scores to create the overall D score, DT. A positive D score indicates a strong positive association with the target indicators.

Individualized Balance Scores

Individualized Balance Scores (IBID)

Manuscript in progress, Schultz, Woodcock, Hernandez

- Continuous variable (-1 to 1) calculated from all 3 sides of each balance triangle
  - D-Scores for Implicit
  - Composite scores for Explicit
- Positive scores = balanced profiles
- Negative scores = imbalance profiles
- Closer to 0 = greater variability in individual scores

Utilizing the Balanced Identity Theory, the current study employs a new methodology of calculating individualized balance scores for implicit and explicit associations. Full details of the formulation and validation of this new method of calculating balance scores can be found in the supplemental slides at the end of this presentation if anyone is interested. Balance scores were calculated using either 3 of the IATs or the 3 explicit scales. Scores that are positive represent balanced profiles, while negative scores represent imbalance profiles. Larger scores represent less variability at the individual level across the three legs of the triangle, while scores closer to zero represent individuals with greater variability in their 3 scores.

PRELIMINARY ANALYSES

Prior to substantive analyses, the data was screened and cleaned and preliminary analyses were conducted.

Data Prep & Assumptions

- ✓ Little's MCAR test for missingness ($\chi^2_{df=4}$= 7.55, *p* = .11)
- ✓ No concerning outliers (AV Plots, Leverage, Studentized Residuals, Cook's D)
- ✓ Normality: Shapiro-Wilks (*z* = 2.56, p < .05), no concerns with Density or QQ-plots, residuals centered around zero with SD near 1, not significantly skewed (χ^2=5.06, *p*=.17) or kurtotic (χ^2=1.49, *p*=.22)
- ✓ Homoscedasticity: Cook-Weisberg (χ^2=.03, *p* =.87), Cameron & Trivedi (χ^2=4.09, *p* =.54)
- ✓ Greenwald (2002) 4-Test balance congruity assumptions: no concerning violations

Missing data were first examined to determine if data were missing completely at random (MCAR), as standard of a longitudinal study. The Little's MCAR test was non-significant, suggesting missingness in the data were not contingent upon any one variable.

AV plots, leverage values, studentized residuals, and Cook's D values were then reviewed to determine if there were any significant outliers. There were no outliers of concern.
Normality and homoscedasticity were then checked via density and QQ-plots, Shapiro-Wilks tests, and Cook-Weisberg test for heteroskedasticity. Using this holistic approach, the data appeared normal, not significantly skewed or kurtotic, and was homoscedastic.

Lastly, following the balance congruity assumptions laid out by Greenwald and colleagues, IAT data were analyzed using the four-step test. There were no concerning violations within the regressions, so we carried on with analyses.

Descriptive Statistics

		MALES		FEMALES		
		M	SD	M	SD	α
EXPLICIT	GENDER ID	3.34	1.03	3.91	1.03	0.81
	STEREOTYPE ENDORSEMENT	3.87	2.26	5.82	1.68	0.88
	STEM ID	3.84	0.70	4.06	0.72	0.79
	STANDARDIZED BALANCE	0.19	0.79	0.48	0.71	
IMPLICIT	GENDER ID	0.80	0.52	0.57	0.55	
	STEREOTYPE ENDORSEMENT	0.52	0.55	0.34	0.56	
	STEM ID	0.57	0.56	0.56	0.55	
	STANDARDIZED BALANCE	0.42	0.58	0.32	0.67	

Prior to our formal analysis we looked at the descriptive statistics of each of the explicit and implicit measures.

Descriptive Statistics

		MALES		FEMALES		
		M	SD	M	SD	α
EXPLICIT	GENDER ID	3.34	1.03	3.91	1.03	0.81
	STEREOTYPE ENDORSEMENT	3.87	2.26	5.82	1.68	0.88
	STEM ID	3.84	0.70	4.06	0.72	0.79
	STANDARDIZED BALANCE	0.19	0.79	0.48	0.71	
IMPLICIT	GENDER ID	0.80	0.52	0.57	0.55	
	STEREOTYPE ENDORSEMENT	0.52	0.55	0.34	0.56	
	STEM ID	0.57	0.56	0.56	0.55	
	STANDARDIZED BALANCE	0.42	0.58	0.32	0.67	

Each of the measures, the gender identity, stereotype endorsement, and stem identity, all had acceptable reliability values. This can be seen in the column marked alpha. All alpha values are around or above .80.

Descriptive Statistics

		MALES		FEMALES		
		M	SD	M	SD	α
EXPLICIT	GENDER ID	3.34	1.03	3.91	1.03	0.81
EXPLICIT	STEREOTYPE ENDORSEMENT	**3.87**	2.26	**5.82**	1.68	0.88
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EXPLICIT	STANDARDIZED BALANCE	0.19	0.79	0.48	0.71	
IMPLICIT	GENDER ID	0.80	0.52	0.57	0.55	
IMPLICIT	STEREOTYPE ENDORSEMENT	0.52	0.55	0.34	0.56	
IMPLICIT	STEM ID	0.57	0.56	0.56	0.55	
IMPLICIT	STANDARDIZED BALANCE	0.42	0.58	0.32	0.67	

One trend we note here is that women had a higher explicit stereotype endorsement of men being correlated with STEM rather than gender neutrality or the inverse opinion of women being strongly associated with STEM. This was conducted with a scale of 1 to 7.

Descriptive Statistics

		MALES		FEMALES		
		M	SD	M	SD	α
EXPLICIT	GENDER ID	3.34	1.03	3.91	1.03	0.81
	STEREOTYPE ENDORSEMENT	3.87	2.26	5.82	1.68	0.88
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	STANDARDIZED BALANCE	0.19	0.79	0.48	0.71	
IMPLICIT	GENDER ID	0.80	0.52	0.57	0.55	
	STEREOTYPE ENDORSEMENT	0.52	0.55	0.34	0.56	
	STEM ID	0.57	0.56	0.56	0.55	
	STANDARDIZED BALANCE	0.42	0.58	0.32	0.67	

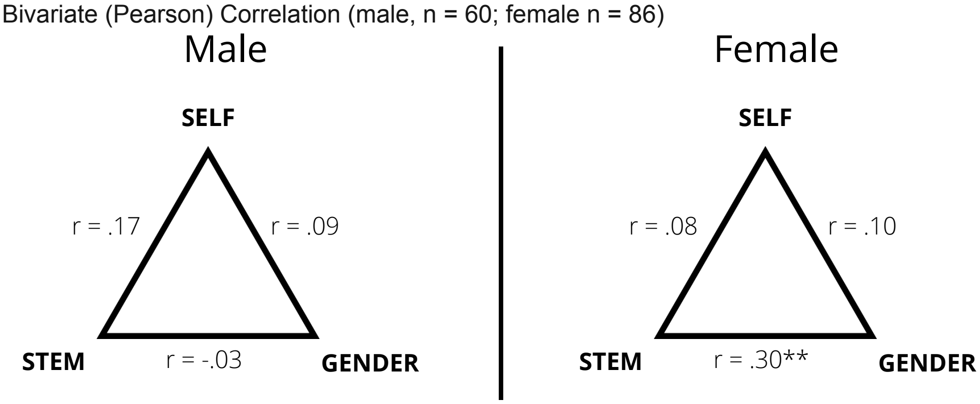
As for explicit balance overall, we can see that women in the study have higher explicit balance scores than their male counterparts. Implicit balance scores were near equal for men and women.

The next step is to then see if there are differences in their scores based on which STEM major they are in, which is what we will focus on in our regression analysis.

Bivariate Correlations of Implicit and Explicit Measures

Implicit identities are not correlated with their explicit counterparts

Results: Bivariate (Pearson) Correlation (male, n = 60; female n = 86)



To address the previously mentioned inconsistencies in the literature around the relationship between implicit and explicit measures, initial bivariate pearson correlations were conducted. These correlations found no relationship between implicit and explicit legs of the balanced identity triangle for males, but females had moderate positive correlation between implicit and explicit gender stereotype endorsement ($r = .30$, $p<.01$). However, further regression analyses revealed no significant moderation by gender for the balance scores.

RESULTS

Next, we wanted to look into this relationship further based on teasing out the nuances of STEM disciplines. Particularly by separating STEM disciplines into historically numerically equal (eg. Sciences such as Biological and Life Science) and those that are historically male-dominated, such as Engineering and Computer Science, to see if a moderation by gender existed within these subgroup. It is important to note that, while all sciences may not be represented equally by males and females, the majority of this sample who were in science were in Biological or Life Science, therefore they were grouped together for ease of analysis.

Are there differences between Majors in implicit/explicit balance scores varying by participant gender?

2-Step Sequential Regression

Biological/Life Science (Sci) vs. Engineering/Computer Science (Eng/CS)
Moderation by Gender

Results - **Implicit Balance**

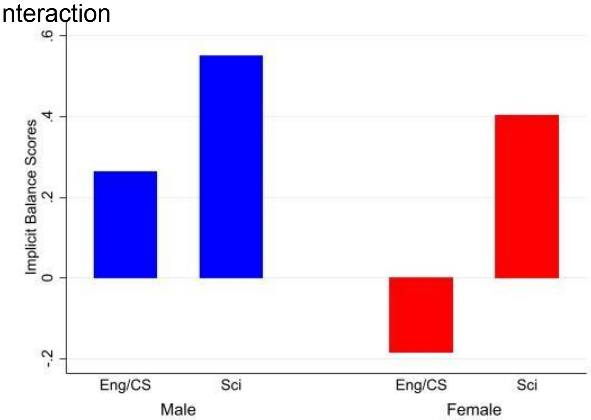
Step 1: Gender, Major

$F_{2,143}$ = 6.21**, R^2 = .08

Step 2: Gender by Major Interaction

Non-significant

(*b* = .30, p = .22)



A two-step multiple regression analysis was conducted to determine, first, if implicit balance scores varied as a function of female status or Science major status. Gender and Major were entered into the first step, where together they explained a significant portion, about 8%, of the variance in implicit balance scores. Next, the gender by major interaction term was entered into step to. The change in variance explained between step 1 and step 2 was non significant, suggesting that the difference of differences was non-significant. However, if you look at the simple slopes graph, we can see that all males, regardless of which STEM major, had a more balanced implicit score, while females in engineering and computer science had negative implicit balance scores and females in science had strong, positively balanced scores. This shows us that, while there is no interaction between gender and major occuring, there is a difference in implicit balance scores based on gender.

Are there differences between Majors in implicit/explicit balance scores varying by participant gender?

2-Step Sequential Regression

Biological/Life Science (Sci) vs. Engineering/Computer Science (Eng/CS)
Moderation by Gender

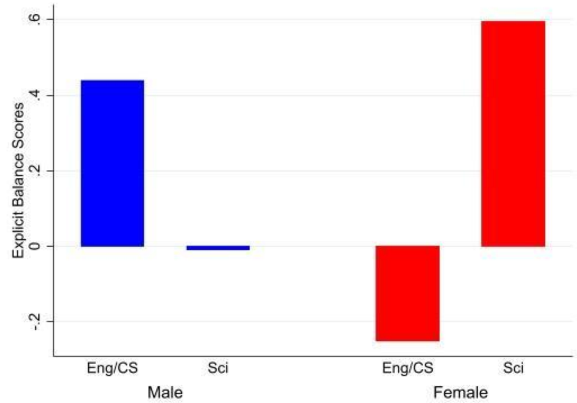
Results - **Explicit Balance**

Step 1: Gender, Major

Step 2: Gender by Major Interaction

$F_{3,142} = 9.10^{***}$, $R^2 = .16$, $\Delta R^2 = .12^{***}$

$\beta = .86$, $b = 1.30$, CI [.74, 1.86]



Next, we looked at explicit balance scores. A similar approach was taken, wherein a 2-step sequential regression was conducted. Here, we see that when the interaction term is entered into step 2, we have a 12% increase in the amount of variance explained in explicit balance scores, variance attributable to the interaction term. The graph here shows that, not only did a similar pattern to the implicit balance scores exist where females in science were balanced but females in engineering/computer science were imbalanced, but males in engineering here had positive explicit balance scores while males in science were near neutral.

Discussion

- Differences in implicit and explicit balance scores based on gender and major

Females in Engineering/Computer Science have imbalanced profiles (both implicit and explicit)

Highlights importance of looking at nuances within STEM as opposed to STEM as a whole

Reinforces the need to utilize both implicit and explicit measures

This study employed a new methodology to calculate balanced identity scores for men and women in undergraduate STEM fields, with the ultimate goal of utilizing these balance scores for predictive purposes in studies focusing on broadening participation. While some STEM fields are numerically equally represented for men and women, such as Biological and Life Sciences, others are still struggling to reach parity. We looked at the differences in implicit and explicit balanced identity scores for men and women in each of these two STEM categories and found that (with this sample of students) females in engineering and computer science have imbalanced profiles, even in their junior and senior years, both with implicit and explicit balance scores. This highlights the fact that STEM may not be able to be looked at as a whole, but rather broken into potential categories where belonging and numerical representation may be a factor. These findings also reinforce the need to utilize both implicit and explicit measures when looking at personal-professional identities, as there were inconsistencies with how men and women responded to explicit scores and how their implicit associations showed up.

Limitations & Future Research

- Cross-sectional in nature
- Not fully generalizable to all STEM students (Juniors/Seniors, primarily Biological/Life Science)
- Construct validity: Stereotype Endorsement

- Ethnic minority differences within STEM
- Gender differences within Engineering disciplines based on numerical representation
- Longitudinal study of Freshman & Sophomores
- Ultimate goal: Study if IBID is predictive of meaningful outcomes (STEM intentions and/or persistence)

As with any study, there are limitations to be considered which lead us to potential future research. This study, although coming from a longitudinal study, only utilized data from one wave. Second, the current study only represents juniors and seniors, a time when most students have overcome the difficulties of freshman and sophomore year where we most often see STEM students depart the major. Our science students were also primarily made up of biological and life sciences students, which is not necessarily representative of all science majors. Lastly, in future studies, we would implement a change to the wording of the stereotype endorsement scale as all participants, regardless of gender, saw it worded the same and scores were reverse coded for women. For consistency sake, we would adapt the wording to match participant identified gender.

Since the primary endeavor of the longitudinal study is to look at balanced identity profiles of two different ethnic groups, we could also see if patterns reflected here for minoritized women in STEM hold true for minoritized ethnic groups in STEM. Additionally, with a much larger sample, it would be interesting to see if there are differences in balance scores between gender groups within Engineering disciplines, as some engineering disciplines have different numerical representation of women (such as Electrical Engineering compared to Biomedical Engineering). We would also be interested in seeing how these balance scores change or shift over time starting in freshman year and continue on through graduation.

Ultimately, the goal of utilizing these individualized balanced identity scores is to determine if they can be predictive of outcomes that are meaningful to this type of research. Specifically, we care to see if IBID scores can be used to determine STEM intentions and persistence.

Conclusion

As researchers continue to investigate the nature of identity development throughout one's academic journey surrounding prevailing stereotypes in STEm fields, our study suggests the importance of utilizing multiple measures personal-professional identities. Specifically, we highlight the need for teasing out the nuances of variances in identity due to gender as well as the numerical representation of different STEM fields, as opposed to viewing STEM as a whole.

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Here is the list of references cited throughout this presentation.

Questions?

We would be happy to take any questions you might have at this time and thank you for listening.

Supplemental Slide

Individualized Balance Scores (Supplemental)

Individualized Balance Scores formulated based on the following criteria:

1) Needed to replicate Greenwald's discrete categorization of balance/imbalance
2) Includes all three legs of the balance triangle
3) Needed to capture and quantify variability in their scores and reward those who had homogeneity and penalize those with variability in their scores

Individualized Implicit Balance Scores (IBID; Manuscript in progress, Schultz, Woodcock, Hernandez):

$$ibr_{implicit} = D_{Gender\ ID} * D_{STEM\ ID} * D_{Stereotype\ Endorsement}$$

$$IBID_{implicit} = ibr_{implicit}/(|ibr_{implicit}| + (|ibr_{implicit} * sd(ibr_{implicit})|)$$

Individualized Explicit Balance Scores: Proportion of Maximum Scores (POMS; Little, 2013)

$$ibr_{explicit} = cPOMS_{Gender\ ID} * cPOMS_{STEM\ ID} * cPOMS_{Stereotype\ Endorsement}$$

$$IBID_{explicit} = ibr_{explicit}/(|ibr_{explicit}| + (|ibr_{explicit} * sd(ibr_{explicit})|)$$

Utilizing the Balanced Identity Theory, the current study employs a new methodology of calculating individualized balance scores for implicit and explicit associations. IBID, or Individualized Implicit Balance Scores, are calculated by first multiplying each of the D scores from each IAT to create the individual balance numerator (ibr). Then, the ibr is divided by the sum of the ibr plus the ibr multiplied by the standard deviation of the ibr. Balance scores range on a scale from -1 to 1, with negative scores representing imbalance profiles and positive scores representing optimally balanced profiles. Similarly, explicit balanced scores are calculated. Prior to calculating the ibr, each explicit score is transformed into Proportion of Maximum Scores so that scales are on a standard metric of 0 to 1. The same method as implicit is then implemented to calculate the explicit balance scores, again ranging from -1 (imbalanced) to 1 (optimally balanced).