

# Using the S-STEM Programmatic Lens to Investigate Equity in a Computer Science Department

Sarah Hug  
Colorado Evaluation & Research Consulting  
Westminster, CO 80021  
[hug@colorado.edu](mailto:hug@colorado.edu)

Tom Carter  
Computer Science Department  
California State University, Stanislaus  
One University Circle  
Turlock, CA 95382  
[tcarter@csustan.edu](mailto:tcarter@csustan.edu)

Mark McKay  
Colorado Evaluation & Research Consulting  
Westminster, CO 80021  
[Mark.mckay.cerc@gmail.com](mailto:Mark.mckay.cerc@gmail.com)

Melanie Martin  
Computer Science Department  
California State University, Stanislaus  
One University Circle  
Turlock, CA 95382  
[mmartin@csustan.edu](mailto:mmartin@csustan.edu)

Megan Thomas  
Computer Science Department  
California State University, Stanislaus  
One University Circle  
Turlock, CA 95382  
[mthomas@csustan.edu](mailto:mthomas@csustan.edu)

**Abstract**— In this paper, we describe how the programmatic lens of S-STEM, centered on transfer students and newly enrolled students with financial need and proven achievement, provided a context to study course taking and retention patterns in a mid-size computer science department at a regional state university before and since the beginning of the S-STEM grant, which is currently in its 5<sup>th</sup> year. Our research utilizes QuantCrit theory, taking a critical stance towards data analysis and the interpretation of achievement and course taking data from a perspective that acknowledges how power and oppression shape opportunity and outcomes for students. We detail how the findings are interpreted in relation to S-STEM program impacts, first by the research team, and then in collaboration with the faculty stakeholders. We also consider how the findings can be used for departmental action to further the aims of S-STEM beyond the years of the grant.

**Keywords**—Critical Theory, S-STEM, Departmental Culture, Student Outcomes, Equity Lens

## I. INTRODUCTION

Underrepresentation of women and students of color in science, technology, engineering, and math is a national epidemic. The lack of socioeconomic, gender, and racial/ethnic diversity in computer science is particularly pronounced—only 11% of recent computing graduates were women, while Hispanics comprised only 7% of all Bachelor degree earners [1]. Ethnic minorities who are also the first in their families to attend college are less likely to graduate than their peers, especially when they experience a lack of peer support to achieve in higher education [2]. Cocurricular and informal learning opportunities can provide students access to expert thinking in their disciplines, and can improve retention in the sciences [3]. Scholarships for science, technology, engineering and math (S-STEM) programs were designed to provide curricular, co-curricular, and financial support to students with financial need who are underrepresented in STEM fields. Results from S-STEM program indicate scholars experience greater retention and higher achievement than their peers, [4,5,6] yet little is known about how S-STEM scholarship programs influence student outcomes at the departmental level, or how S-STEM programs mitigate systemic forms of oppression, such as racism

and sexism, that plague education in the western world, particularly in STEM fields [7]. This study is an exploratory investigation of the computer science department at CSU Stanislaus. Through an equity lens, the study looks at student level variables to understand patterns of student success as they relate to social identifiers of underrepresentation in STEM.

## II. THEORETICAL FRAMEWORK

Our theoretical framework brings together two lenses from the social sciences: sociocultural learning theory [8-12], and critical race theory [13-16]. In this section we describe how our understanding of the S-STEM program relies on the intersection of these theories, and how we designed our research to practice study to interrogate questions relevant to each.

In our view, learning and development occur as students interact with their peers, take up artifacts, language, and tools of practice, and when they engage with more knowledgeable others [8-12]. In other words, we consider learning to be social. This understanding of learning suggests pedagogical practices that are active and interactive—we highlight elements of the S-STEM program as examples of this understanding of the social aspects of learning in later sections. We acknowledge that opportunities to learn are not uniformly granted to all students, particularly in higher education where power structures evident in the system are designed for certain individuals with privileged status to thrive [13]. In the case of computer science, historically in US contexts those have been white and Asian males who are well funded to attend college and are not the first in their family to enroll in higher education [17].

As we looked at quantitative data from the computer science department at CSU Stanislaus, we were considering the ways in which power and privilege shape student outcomes in higher education, and how power and privilege have strong ties to gender, racial/ethnic identifiers, socioeconomic status, and class. Critical theory and QuantCrit [16] in particular demand that as we make comparisons across students of different groups we name the systemic oppression that creates the uneven playing

field when we do find differences. Rather than describe students from underrepresented groups as performing more poorly than students who are from dominant groups, we acknowledge the institutional and cultural forms of oppression at work to create that difference (sexism, classism, racism). In this way, we disrupt the dominant narrative that subgroups of students are less capable of succeeding in computer science based on social identifiers such as gender, race, and class. Instead, we consider the systemic influence of factors that impact groups of students differentially, and in some cases impact at the intersection of multiple systems of oppression [15].

#### *A. Application of relevant theory to the S-STEM program at UNIV.*

The NSF S-STEM program is designed explicitly to address inequity in STEM degree production through what critical race theorists would call distributive justice. This strategy focuses on providing access to resources that students currently lack, such as funding for college achievement, as well as access to academic and professional resources such as mentoring, peer cohorts, research opportunities, and professional conference engagement. While the former is essential to persistence in a four-year degree in STEM, the latter may be essential for successful career outcomes following graduation.

S-STEM grants are designed not only to support individuals who qualify for the scholarship (Pell grant eligible students in good academic standing, with an emphasis on students who would be considered underrepresented in the fields). In fact, the goal of S-STEM projects locally is to influence the department as a whole in some way. While the S-STEM call for proposals is not explicit on this point, the local stakeholders at Stanislaus have considered how the work of S-STEM can change the departmental culture to support more (and more kinds of) students to succeed in computer science. We consider data from the department as a whole as an opportunity to understand department culture, and the ways in which systemic racism, classism and sexism might influence student outcomes.

The questions we addressed in this Research-to-Practice study were:

1. How did S-STEM student outcomes compare with their peers' outcomes in computer science at UNIV?
2. How do student outcomes differ due to effects of sexism and racism in computer science at UNIV?
3. How do financial and familial educational differences influence student outcomes in computer science at UNIV?
4. How can the department incorporate statistical findings into improved, more equitable educational practice?

In spring 2020, the researchers made a data request to the Institutional Research (IR) office at CSU Stanislaus. The dataset was to include de-identified student level data for all students who had a declared computer science major from Fall 2014 through the fall 2019 semester. The data set included social identifiers such as ethnicity, race, gender, first generation status, Pell grant eligibility, and transfer or first entry status. The IR office was able to mark S-STEM student as a variable as well, based on the submission of a list of students to the data extractors at the time of the request. The request asked for major and GPA

at regular intervals (e.g., the spring of each year) to track movement out of the major. In addition, faculty selected courses they found to be important for retention and success in the major. Not surprisingly, many of the courses chosen were math courses, as these often serve as gatekeeper courses in engineering and science majors [18].

We chose outcome variables that have real consequences and are incrementally useful, specifically grades earned in courses needed in the major, cumulative GPA, and retention in the major. As students in the database spanned multiple years of study and multiple cohorts, we broadened the notion of "success" from graduation in the major to graduation and/or persistence in the major. As such, we considered variables consequential to success in computing career success, the cumulative GPA and retention in the major. Course level grade differences were measured across all social identifiers indicated as potentially related to power and privilege in the CS department- gender, underrepresented minorities (URM), Pell grant eligibility, transfer status, and first generation in college status.

Our main goals were to be descriptive about the current state of the department rather than to predict student differential outcomes over time. For the most part, we chose simple comparative statistics—Chi squares, t-tests—to describe current differences and similarities among student groups. We began our analysis with S-STEM students at the center, then broadened to understand the department as a whole.

#### *Exploratory Data Analysis*

First, S-STEM student outcomes were compared with peers in the major. Second, the S-STEM students were compared with a peer group of students succeeding in entry level computer science at UNIV. Following these program specific comparisons, authors 1 and 2 began analysis utilizing the hypotheses that societal biases and hierarchies of power may be at work in the ways in which students continue (or choose not to continue) in computer science at UNIV. The second author utilized each variable related to privilege to compare student groups on each set of outcome variables (course performance, cumulative GPA, and retention/graduation in the major).

We recognize the intersectionality of student social identifiers—student identities are not monolithic—individuals represented in our dataset are both Latina and female, for example, or transfer students and first-generation students. Unfortunately, our department level dataset did not include a large enough sample to analyze across multiple variables.

Following a first run of data, social science researchers, authors 1 and 2, shared findings with departmental stakeholders to gather feedback. In this meeting, the stakeholders suggested additional study, in particular for comparing transfer and first-time students. These changes are reflected in the results section below.

### III. CONTEXT OF THE STUDY

The context of the study is vital to interpretations made locally and to any generalizations a reader might make to like settings [19]. This study is set in the context of CSU Stanislaus, a regional state university in a rural western agricultural valley

in the United States. The institution has a Hispanic population of 56% across all majors and has 65% female enrollment. These figures are not mirrored in the composition of the computer science department, in which 14% of students in the dataset are women and only 41% Hispanic. This is a common finding in STEM departments at Hispanic Serving Institutions (HSIs) [20]—parity is uncommon as racism and sexism continue to constrain underrepresented individuals’ identification with STEM fields even at minority-serving institutions.

#### A. S-STEM Program Design

At CSU Stanislaus, students who earned the S-STEM scholarship may have matriculated from one of the nearby community colleges, a partnering institution on the NSF grant. Others were first-time students. Students met weekly with at least one of three faculty in the department and with their cohort of Scholars. As transfer students matriculated, they integrated with their appropriate cohort of Scholars who were first time attendees at CSU Stanislaus. Meetings shifted over the years—in the first year of the program participants met to learn about research projects of interest to the faculty. By the second year, students participated in problem solving courses [21] with content targeted to students of different cohorts. For example, introductory problem solving courses covered guidance and practice for approaching problems systematically, while advanced problem solving involved technical interview preparation and practice with content related to data structures.

Each year prior to 2020, students attended Great Minds in STEM conference together. At this event, they networked with industry representatives who coached them on how to prepare for interviews, build resumes that attract attention, and practice their interview skills. They also met students from HSIs across CAHSI. Over the course of the grant, multiple participants earned internship and/or job opportunities based on experiences at the conference. In 2020, the event was held virtually because of the global pandemic. All scholars were expected to attend individually.

### IV. RESULTS

#### A. S-STEM student comparisons

S-STEM students are chosen to receive scholarships based on multiple elements of their application—one of these elements is their previous academic achievement. When S-STEM students are compared at the course level with all of their peers majoring in computer science, we find a marked, and statistically significant difference in their grades ( $p < .00$ ). In addition, we find a statistically significant difference in the proportion of S-STEM students who remain in the major [ $\chi^2(1, N=905) = 6.28, p < .01$ ], and in the current and/or final GPAs obtained by this group by spring of 2020. See table below.

Subgroup Identifier	Comparison Between S-STEM and non-S-STEM Students		
	Number in comparison group	Current/Recent GPA	Percent Retained in Computer Science
S-STEM	36	3.28**	80.6%**
Non-S-STEM	869	2.86**	59.7%**

#### B. S-STEM comparative subgroup of achieving students

As S-STEM scholarships are awarded based on both merit and need, it was important to establish a comparison group within the IR data that was comparable to the S-STEM students through a measure of merit. As SAT and ACT scores were not readily available for all students, we chose to emphasize course success in some of the entry level courses as a place to start to develop a comparison group. The comparison group was a subset of non-S-STEM students who had successfully completed at least 2 of the first 4 courses needed in the major with an A or a B. There were 177 students who fit into this category. When S-STEM students were compared to the high achieving comparison group, there were no statistically significant differences in GPA, however S-STEM students were more likely to remain in the major—this difference approached, but did not reach, statistical significance (Chi square 2.317,  $p < 0.10$ ).

Subgroup Identifier	Comparison Between S-STEM and non-S-STEM high achieving subgroup		
	Number in comparison group	Current/Recent GPA	Percent Retained in Computer Science
S-STEM	36	3.28	81%
Non-S-STEM high achieving group	177	3.24	68%

The high achieving comparison group was markedly different in terms of student social identifiers, as may have been expected given the targeted recruitment of S-STEM scholars from groups underrepresented in the field. Comparative analysis indicates the high achieving student comparison group students were less likely to be Hispanic (41% compared with 69% in S-STEM, Chi square 11.95,  $p=0.000$ ), less likely to be women (15% compared with 30% in S-STEM, Chi square 4.7785,  $p=0.029$ ), and slightly less likely to be first generation students (61% compared with 75% in S-STEM, Chi square not statistically significant at 2.317).

As expected, S-STEM students who are selected based on both need and merit were more successful than non-S-STEM students who were more variable in terms of success in the major. When S-STEM scholars were compared with a group of high achieving students in the department, we find a) that the comparison group is less diverse, and b) the differences in outcomes are no longer significant.

#### C. Influence of Systemic Racism on Student Outcomes

Student outcomes were compared among students who were from racial/ethnic groups identified as underrepresented in the computer science field using Institutional Research data. The social identifier of “URM” indicates the student comes from an underrepresented racial or ethnic group, and the “non-URM” identifier indicates students who are identified as having privilege in the field through their racial/ethnic makeup. In the CSU Stanislaus context, URM student populations are primarily Hispanic/LatinX, though a significant portion (approximately 7%) of the student body are identified as African American/black, more than one race, Native American, Native Hawaiian or Pacific Islander in the computer science student database.

Course	URM pass rate (n= X)	Non-URM pass rate (n= X)
Math 1080	78%	80%
Math 1100 Precalculus	68%**	80%
Math 1600	91%	94%
Math 1620	100%	93%
Math 1410 Calculus	67%**	78%
Math 1420	68%	75%
Math 2300	84%	86%
CS 1500	88%	90%
CS 2500	89%	90%
CS 2700	91%	91%

We notice course-level differences for URM students in some math courses, yet these differences are narrower in computer science courses, and in some cases non-existent. The table above shows math course differences in pass rates as high as 12% such as in Math 1100, and 11% in Math 1410, both of which show statistically significant differences.

Social Identifier	Comparison Between URM and non-URM Students		
	Number in comparison group	Current/Recent GPA	Percent Retained in Computer Science
URM	424	2.78**	60.6%
Non-URM	481	2.96**	60.5%

The overall GPA mean for URM students is lower, and this difference is statistically significant, indicating a significant effect of racism on student outcomes at CSU Stanislaus. Despite the lower average GPA, URM students have been just as likely to stay in the major than their more privileged counterparts.

#### D. Influence of Systemic Sexism on Student Outcomes

The gender comparison data was mixed, and yet the results mirror what we know from qualitative and mixed methods studies of women in STEM—while women tend to outperform men in STEM fields they are more likely to leave the field than men [22].

Subgroup Identifier	Comparison Between Women and Men, as Defined by IR Office Data		
	Number in comparison group	Current/Recent GPA	Percent Retained in Computer Science
Women	149	2.96	55.0%
Men	756	2.86	61.6%

#### E. Financial Elements of Student Outcome Difference

S-STEM students are those who are Pell-grant eligible. This variable was chosen as a comparison variable to understand how those who experience a significant lack of funds compare academically to their peers. We note slight differences in GPAs and in percentages of students who are retained in the major, though neither of these gaps rise to the level of statistical significance.

Subgroup Identifier	Comparison Between Pell eligible and non-Pell Students		
	Number in comparison group	Current/Recent GPA	Percent Retained in Computer Science
Pell	518	2.84	58.2%
Non-Pell	387	2.92	61.7%

#### F. Familial College Experience and Student Outcomes

Having a parent or parental figure who attended college affords a lot of advantage to students—understanding of higher education systems, policies, and funding opportunities privilege those whose families have experience in the system. Our study of students who are the first in their family to go to college indicates the influence of this vicarious experience may influence GPA slightly, while those who are first gen were slightly more likely to be retained in the major.

Subgroup Identifier	Comparison Between First Gen and Continuing Gen Students		
	Number in comparison group	Current/Recent GPA	Percent Retained in Computer Science
First Gen	603	2.84	61.2%
Contin. Gen	302	2.94	59.3%

#### G. Difference by Entry Status- Unexpected Outcomes for Transfer Students

Entering a 4-year college directly as a first year student was hypothesized to be more advantageous to sticking with the major, yet our results indicate those who had transferred were more likely to persist in computer science. As a way to account for experience in college when comparing transfers (often entering as juniors) with those who begin as freshmen in the major, the analysis was restricted to students who had successfully completed CS 2700. Results in the table below confirm that transfer students are more likely to persist in the major. This is a surprising finding—it is unclear how strong articulation policies enacted in the California university system contribute to the success of the transfer students.

Subgroup Identifier	Comparison Between First Gen and Continuing Gen Students		
	Number in comparison group	Current/Recent GPA	Percent Retained in Computer Science
Transfer	327	3.04**	73%**
First time, completed CS 2700	246	2.79**	53%**

#### H. Exploring Simple Linear Regression to Predict Student Success

As departments work to support student success, it is useful to consider what variables appear to predict, or at least correlate with, student overall GPA. As part of our effort to understand student outcomes in the CSU Stanislaus computer science department, we focused on near-term outcomes that we

hypothesized could influence student overall GPAs, either at graduation or at the level at which they were completing courses as of spring 2020.

The following predictor variables were used in exploratory regression analyses: SAT math score, Calculus grade, and discrete structures grade. The dependent variable was current/graduating GPA in computer science. We note the second and third comparisons were not independent, as each course's grade influences cumulative GPA. However, we found the potential for understanding relationships among gatekeeper courses worthwhile for study.

A simple linear regression was calculated to predict current/graduating GPA based on SAT math score. A significant regression equation was found ( $F(1, 310) = 24.195, p < .000$ ), with an  $R^2$  of .072. Participants' GPA increased 0.003 for each point on the Math SAT. The math SAT score accounted for only 7% of the variability in current/graduating GPA.

When the independent variable is selected as the Calculus course grade, a significant relationship can be found with the recent/graduating computer science GPA for students at UNIV. The regression equation was significant ( $F(1, 292) = 104.881, p < .000$ ) with an  $R^2$  of 0.264. Participants' cumulative GPA rose by 0.234 with each point in the Calculus course grade. The model predicted 23% of the variance in GPA.

Finally, the discrete structures course grade was selected to understand how this course predicted cumulative GPA. The regression equation was significant ( $F(1, 354) = 384.34, p < .000$ ) with an  $R^2$  of 0.521. The discrete structures course grade predicted 52% of the variance in current/graduating GPAs.

#### *1. Interpretation of Quantitative Data in Light of Qualitative Data from S-STEM*

It is clear from our quantitative results of Institutional Research data that S-STEM students are more successful than their peers when it comes to retention in the CS major as well as in relation to their cumulative GPA. When compared to similarly high achieving peers, S-STEM students have similar cumulative GPAs, but are more likely to persist in the major. In this section, we posit why S-STEM students are more successful, even as many of them confront systemic gender and racial bias in their education.

##### *1) Greater opportunity to participate in informal computing networks*

In interviews, students describe how their increased access to conferences and other informal learning experiences like clubs and hackathons influence their knowledge of their field, their identification with different aspects of computing, and their dedication to the major. This may influence the rate at which S-STEM students remain in the CS department rather than drifting towards different fields.

##### *2) More time to work on academics, rather than work for pay*

Most students who earn the S-STEM grant describe how they either lessen the number of hours they work at a paid position or indicate they no longer seek out paid work during their schooling. Interview data suggest that students are able to devote more time to their studies, including formal education

such as coursework and cocurricular educational opportunities such as undergraduate research. This shift of time towards academics may influence achievement in CS.

##### *3) Recognition in the field boosts computer science identification*

Qualitative data from the S-STEM project indicate that students view obtaining the S-STEM grant as validation of their interest in the field. For example, when students are asked in interviews about the accomplishment of which they are most proud, many report the S-STEM scholarship itself. Recognition is an element of STEM identity described in the literature on learning in science, and we hypothesize that earning the scholarship may support student persistence in the field.

##### *4) Faculty mentoring supportive of student learning*

Interview data suggests faculty mentoring is improved with participation in S-STEM. Scholars describe how the frequent interaction with S-STEM faculty leads increases comfort with professors, and creates opportunities for students to ask about coursework, informal and co-curricular opportunities, as well as to get guidance on computer science concepts. The connections to faculty may support achievement as well as persistence in the field.

##### *5) Cohort of high achieving students, from CC to 4 year*

Students meet their S-STEM colleagues in regular meetings on campus, and as the community college students transfer to CSU Stanislaus, they join their peers who originated at the 4-year institution. The S-STEM scholars credit their peers with supporting their learning both inside and outside of class, and some describe their cohorts as supportive to their persistence in the major.

## V. DISCUSSION AND FUTURE WORK

As departmental stakeholders begin to apply these findings to their understanding of their student body, we envision formal and informal implications may arise. As we review findings that relate to racism, for example, it appears that computer science is more equitable in student outcomes than math coursework appears, and it would be valuable to understand how the fields differ in supporting student success. One faculty member noted the extent to which discrete structures course success appears to correlate with cumulative GPA, and wondered aloud if the department might develop a pathway that allows for students to reach the course more quickly to support success in the major. The department may choose to learn more about the transfer/first time entry student differences uncovered in this deep dive into Institutional Research data. Some policy decisions have already been in place institutionally to deemphasize the role of high-stakes test scores in access to higher education, which is bolstered by the finding that math SAT scores in our dataset account for only 7% of the variability in cumulative GPA for our student population.

This study emerged from an S-STEM scholarship program at UNIV, and was intended to do the following: a) understand how social identifiers including gender, ethnicity/race, familial income, transfer status, and familial experiences with higher education constrain and afford student success, b) reframe comparative success outcomes in critical terms, as evidence of sexism and racism and other forms of inequity, rather than as

deficits in students; and c) hypothesize factors that may influence S-STEM student success, based on complimentary qualitative data.

The data reported here were collected just before the COVID-19 pandemic changed higher education in the spring of 2020. In future work, we hope to understand whether and how the pandemic influenced students' success, and particularly whether the pandemic unevenly impacted students already underrepresented in the field.

#### ACKNOWLEDGMENT

This paper was written from support from NSF Award # 1643944. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

#### REFERENCES

- [1] ANONYMOUS (2016).
- [2] Dennis, J. M., Phinney, J. S., & Chuateco, L. I. (2005). The role of motivation, parental support, and peer support in the academic success of ethnic minority first-generation college students. *Journal of college student development*, 46(3), 223-236.
- [3] Eagan Jr, M. K., Hurtado, S., Chang, M. J., Garcia, G. A., Herrera, F. A., & Garibay, J. C. (2013). Making a difference in science education: the impact of undergraduate research programs. *American educational research journal*, 50(4), 683-713.
- [4] Anderson-Rowland, M. R., et.al., (2012). Leveraging S-STEM scholarship programs. In 119th ASEE Annual Conference and Exposition. American Society for Engineering Education.
- [5] Kalevitch, M., Maurer, C., Badger, P., Holdan, G., Iannelli, J., Sirinterlikci, A., & Bernauer, J. (2012). Building a community of scholars: one University's story of students engaged in learning science, mathematics, and engineering through a NSF S-STEM grant. *Journal of STEM Education: Innovations and Research*, 13(4), 34.
- [6] Bruning, M. J., Rover, D. T., & Williams, A. M. (2011, October). Work in progress— Developing engineers for 2020—An innovative curricular and co-curricular approach. In *Frontiers in Education Conference (FIE)*, 2011 (pp. S4D-1). IEEE.G.
- [7] Van Dusen, B., & Nissen, J. (2020). Associations between learning assistants, passing introductory physics, and equity: A quantitative critical race theory investigation. *Physical Review Physics Education Research*, 16(1), 010117.
- [8] Lave, J., & Wenger, E. (1991). *Situated learning: Legitimate peripheral participation*. New York, NY: Cambridge University Press.
- [9] Wenger, E. (1998). *Communities of practice: Learning, meaning, and identity*. Cambridge university press.
- [10] Barton, A.C. and E. Tan, We Be Burnin'! Agency, Identity, and Science Learning. *Journal of the Learning Sciences*, 2010. 19(2): p. 187-229.
- [11] Bell, P., Tzou, C., Bricker, L., & Baines, A. D. (2012). Learning in diversities of structures of social practice: Accounting for how, why and where people learn science. *Human Development*, 55(5-6), 269-284.
- [12] Mejia, J. A., Wilson, A. A., Hailey, C. E., Hasbun, I. M., & Householder, D. L. (2014). Funds of knowledge in Hispanic students' communities and households that enhance engineering design thinking. In *Proceedings of American Society for Engineering Education Annual Conference* (pp. 1-20).
- [13] Solórzano, D. (1998). Critical race theory, race and gender microaggressions, and the experience of Chicana and Chicano scholars. *Qualitative Studies in Education*, 11(1), 121-136.
- [14] Garcia, Nichole M., Nancy López, and Veronica N. Velez. "QuantCrit: Rectifying quantitative methods through critical race theory." (2018): 149-157.
- [15] Gillborn, D., Warmington, P., & Demack, S. (2018). QuantCrit: education, policy, 'Big Data' and principles for a critical race theory of statistics. *Race Ethnicity and Education*, 21(2), 158-179.
- [16] Stage, F. K. (2007). Answering critical questions using quantitative data. *New Directions for Institutional Research*, 2007(133), 5-16.
- [17] National Science Foundation, National Center for Science and Engineering Statistics. 2017. Women, Minorities, and Persons with Disabilities in Science and Engineering: 2017. Special Report NSF 17-310. Arlington, VA. Available at [www.nsf.gov/statistics/wmpd/](http://www.nsf.gov/statistics/wmpd/).
- [18] Bryk, A. S., & Treisman, U. (2010). Make math a gateway, not a gatekeeper. *Chronicle of Higher Education*, 56(32), B19-B20.
- [19] Guba, Egon G. 1981 Criteria for assessing the trustworthiness of naturalistic enquiries, *Educational Communication and Technology Journal*, 2(29): 75-92.
- [20] National Academies of Sciences, Engineering, and Medicine. 2019. *Minority Serving Institutions: America's Underutilized Resource for Strengthening the STEM Workforce*. Washington, DC: The National Academies Press. <https://doi.org/10.17226/25257>. Y. Yorozu, M. Hirano, K. Oka, and Y. Tagawa, "Electron spectroscopy studies on magneto-optical media and plastic substrate interface," *IEEE Transl. J. Magn. Japan*, vol. 2, pp. 740-741, August 1987 [Digests 9th Annual Conf. Magnetics Japan, p. 301, 1982].
- [21] Anonymous, 2020
- [22] Seymour, E. (1995). The loss of women from science, mathematics, and engineering undergraduate majors: An explanatory account. *Science education*, 79(4), 437-473.