Retaining Black Women in Computing: A Comparative Analysis of Interventions for Computing Persistence

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Black women remain severely underrepresented in computing despite ongoing efforts to diversify the field. Given that Black women exist at the intersection of both racial and gendered identities, tailored approaches are necessary to address the unique barriers Black women face in computing. However, it is difficult to quantitatively evaluate the efficacy of interventions designed to retain Black women in computing, since samples of computing students typically contain too few Black women for robust statistical analysis. Using about a decade of student survey responses from an National Science Foundation–funded Broadening Participation in Computing alliance, we use regression analyses to quantitatively examine the connection between different types of interventions and Black women's intentions to persist in computing and how this compares to other students (specifically, Black men, white women, and white men). This comparison allows us to quantitatively explore how Black women's needs are both distinct from—and similar to—other students. We find that career awareness and faculty mentorship are the two interventions that have a statistically significant, positive correlation with Black women's computing persistence intentions. No evidence was found that increasing confidence or developing skills/knowledge was correlated with Black women's computing persistence intentions, which we posit is because Black women must be highly committed and confident to pursue computing in college. Last, our results suggest that many efforts to increase the number of women in computing are focused on meeting the needs of white women. While further analyses are needed to fully understand the impact of complex intersectional identities in computing, this large-scale quantitative analysis contributes to our understanding of the nuances of Black women's needs in computing.

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1 INTRODUCTION

Despite ongoing efforts to diversify computing, Black women remain severely underrepresented in the field. While Black women comprise 7% of the U.S. population [10], they make up only 0.5% of **computer science (CS)** degree awardees [107] and 3% of computing professionals [30]. Compounding this problem is the fact that many (if not most) efforts to diversify the field of computing fail to consider the unique challenges and barriers faced by Black women [85, 92, 104], instead focusing on the effects of either gender or race [55]. Given that Black women exist at the intersection of both racial and gendered identities, tailored approaches are necessary to address Black women's unique needs in computing [69, 88, 102]. However, it is difficult to quantitatively assess which types of interventions work best for Black women, since samples of computing students typically do not have enough Black women in them to produce statistically meaningful analyses on Black women's experiences.

We address this important topic and gap in the literature by conducting a quantitative analysis that focuses on Black women's unique needs in computing. Student survey data was used from the **Students & Technology in Academia, Research, and Service (STARS)** Computing Corps, an alliance funded by the U.S. National Science Foundation's **Broadening Participation in Computing (BPC)** program. STARS is a national network of regional partnerships among higher education, K-12 schools, industry, and community organizations with a shared mission to broaden the participation of women, historically marginalized groups, and persons with disabilities in computing. STARS is a unique BPC program in that it includes a range of engagement interventions shown to increase persistence in computing (i.e., tiered mentoring, service learning and outreach, research experiences, etc.), as opposed to engaging students in a single, uniform intervention.

We use these data to examine the correlation between different types of interventions and Black women's intentions to persist in computing, and how this compares to other students (specifically, Black men, white women, and white men). This comparison also allows us to quantitatively explore how Black women's needs are both distinct from—and similar to—students from other groups that have been historically marginalized. The STARS dataset has two noteworthy features that allow for this analysis: First, it offers a large-enough sample of Black women in undergraduate computing degree programs to be analyzed as a distinct group (as opposed to being lumped in with "women" or "Black students"), and, second, it includes variation in student experiences across multiple interventions (which is necessary for the statistical analysis). For the purposes of this analysis, we use the term intervention to refer to any intentional action taken by any entity (whether or not the entity has been funded by the National Science Foundation) aimed at increasing diversity in computing.

Our analysis contributes to efforts to increase the number of Black women in computing as well as to efforts to improve retention and diversity in computing. To our knowledge, this is the first analysis that quantitatively compares how the same interventions have different relationships with the computing persistence intentions of students who are Black women, Black men, white women, and white men. This provides new insights—above and beyond general prescriptions—on what should be done to retain Black women in computing. It also allows us to quantitatively assess whether Black women's needs have been overshadowed in efforts to increase diversity in computing. In addition, this analysis furthers our general understanding of what kinds of interventions might be best for increasing computing persistence. For instance, does increasing students' leadership skills or improving their collaboration with faculty members have a larger impact on their intentions to persist in computing? Our analysis provides some evidence of which interventions are most effective, while simultaneously examining how a student's racial and gender identity moderates these effects. This reveals important differences between groups and generates discussion about how intersectional experiences relate to the effectiveness of interventions.

We first review the existing literature to explain why we would expect that Black women would have unique needs in the field of computing. We then provide an overview of what BPC programs have done to address the needs of Black women, followed by a detailed explanation of the STARS program interventions. Next, we describe the data from attitudinal surveys collected between 2008 and 2017, our methods, and our results. We conclude with a discussion of our findings and their implications for retaining Black women in computing.

It is important to note the duality of this contribution: While we feel this work is valuable, because it highlights the voices of Black women and brings a quantitative lens to their experiences in computing, our quantitative approach assumes homogeneity within Black women's lived experiences. This is because there was not enough statistical power to create additional categories within the umbrella of being a Black woman (for instance, being a Black woman from a wealthy versus poor household); thus, experiential differences that exist at the intersection of multiple systems of oppression (i.e., socioeconomic status, sexuality, age, disability status, first-generation student, etc.) were not possible to examine in this study. In addition, this analysis explores Black women in computing who have already expressed an interest in computing: Different interventions are likely needed to attract Black women to the field of computing. Thus, while we believe this analysis makes an important and novel contribution to the literature, we do not intend to generalize these findings to all Black women.

1.1 Intersectionality and the Unique Barriers Faced by Black Women in Computing

Intersectionality considers identities like race, gender, class, and other similar categories as socially constructed and best understood together rather than in isolation from one another. In addition, intersectionality is integrative, recognizing that multiple oppressions coexist simultaneously, and these mutually constructing identities underlie interlocking systems of power and oppression [21, 22, 24]. For Black women, this means that, "the intersection of racism and sexism factor into Black women's lives in ways that cannot be captured wholly by looking at the race or gender dimensions of those experiences separately" [24].

So, what does this mean for Black women in computing? Black women in computing face both (1) obstacles that are also experienced by Black men, white women, and/or other marginalized groups and (2) barriers specific to Black women. While space limits us from discussing all the obstacles faced by Black women, we provide an overview of what has guided this work. We draw from both sociological knowledge about gender and racial stereotypes, discrimination, and intersectional identities, as well as research on computing education and **Science, Technology, Engineering, and Math (STEM)** fields.

First, structural disparities disproportionately affect Black students of all genders in the field of computing. The legacy of slavery has led to enduring inequalities for Black people in the U.S., including systematic racism, discrimination, and racial disparities in education, health, social, and economic capital. These external factors "...may limit the extent to which URM [underrepresented minority] students are able to convert their interests into meaningful STEM engagement" [101, p. 17]. In particular, Black students are much more likely to attend racially segregated schools in lower-income neighborhoods with limited funding and resources [27, 83] and are therefore less likely to have exposure to computing before college (i.e., relevant and current curriculums and courses in computer science) [39, 86]. This reduces the likelihood that Black students attend college and pursue degrees in computer science [39, 87]. Even when Black students overcome these barriers to pursue undergraduate degrees in computing, the racial climate on college campuses presents another obstacle [51]. Black students face racism [88], negative racial stereotypes about their intellectual abilities [67, 88], and exclusion from their classmates [12, 15], reducing the likelihood that they complete their degrees and continue in the field of computing [56]. In turn, the dearth of Black professionals in the field of computing makes it more difficult for Back students to receive the formal and informal help needed for success, as Black students are less likely to develop mentor/mentee relationships through which to build social capital and awareness of career opportunities within the computing field [15]. And even with such blatant racial inequality in computing, educators often remain colorblind, for example, blaming underrepresentation on Black students' lack of interest, or finding ways to ignore race altogether as a reason for unequal access to computing education [37, 38].

Second, Black women also face barriers on account of their gender. Women are stereotyped as being worse at male-dominated fields like computing [17, 33, 96]. Controlling for actual competence, research shows that this makes it so that others harbor more doubts about women's abilities and are less likely to treat them with respect and deference in male-dominated fields [33]. These stereotypes also influence students' understandings of themselves, so that women are less likely to view a career in a male-dominated field as consistent with their identity [11], have lower computing self-efficacy and intent to persist than men [7], and are likely to hold themselves to higher performance standards in a male-dominated field, as others will likely to do the same [23, 103]. Indeed, research finds that women self-assess their computing ability lower than men, even controlling for objective measures of ability [46]. Further, highly gender-disparate fields like computing suffer from a scarcity of female role models available to inspire newer generations of women and girls interested in the discipline [17].

Third, Black women also face barriers that are specific to—or heightened by—being Black women. Gendered racial microaggressions in the workplace, school, and other settings negatively impact Black women's mental and physical health [53, 54, 91]. Black women are exposed to more stressful situations than other marginalized groups [3, 43, 74, 94], and Black women's experiences of sexism are compounded by racism-related stress [77]. In addition, Black women are less likely to be heard and their perspectives understood, because they are affected by "intersectional invisibility," in which their experiences are atypical in two primary cultural frameworks: race and gender [81, 88]. In STEM, intersectional invisibility occurs in forms like delegitimization of expertise, being ignored and made to feel one does not belong, and carrying the burden of deciding how to respond and cope with the racialized and gendered hostility [99]. Underlying some of these disparities is the fact that Black women do not reap the "benefits" of benevolent sexism that white women do: while white women are stereotyped as less technically competent than men, they are also stereotyped as in need of protection by men, proper, pure, and ladylike [20]. But Black women are not protected by this benevolent sexism; instead, they face hostile stereotypes that they are angry, promiscuous, welfare queens, and even mammies (among others) [20].

Within the field of computing, this means that Black women face unique hurdles due to the intersection of their marginalized identities [15, 57, 66]. While both Black men and white women face discrimination within the field of computing [35, 89], Black women typically have compounded barriers, as they often face hostility and are stereotyped as particularly inept [15, 79, 80]. Indeed, it is well established that Black women face high levels of mistreatment and microaggressions within computing from both peers and faculty [48]. These include being encouraged by teachers to pursue less challenging disciplines, being left out of peer study groups, and having their input ignored or undermined [80]. In addition, because there are so few Black women in computing, they are often the only Black women in computing spaces [79, 92, 102], which leads to isolation, self-doubt, lack of confidence, and uncertainty about persisting [12, 58, 59, 68].

In response to the need to explore, understand, and address the intersectional identities of Black women specifically within the context of the field of computing, Thomas et al. [92] introduced the concept of an intersectional computing framework. This framework highlights the lived experiences of Black women in computing and sheds light on perceptions that the discipline often renders Black women as invisible, both through a lack of recognition of their contributions and innovations in the computing field, and through exclusion of Black women in samples of participants in studies about women in computing [79, 102]. Despite the many hurdles faced by Black women in computing, they often feel they are not helped by efforts to broaden computing participation, even those aimed at members of historically marginalized groups, as such efforts primarily focus on white women. As one simply put it, “I’m not an URM, I’m a Black woman” [102, p. 224].

The overall effect is that these barriers greatly impact Black women’s persistence and advancement in the field of computing. For instance, a 3-year study of high school students enrolled in a STEM summer program found that gender has a unique negative impact on young women of color despite having similar racial and socioeconomic backgrounds [85]. And while the percentage of women obtaining bachelor’s degrees in computer science has increased overall, the rate of Black women obtaining the same degrees has decreased over 10 years [64].

1.2 Black Women and Efforts to Broaden Participation in Computing

These disparities in representation for Black women in computing have persisted despite over a decade of BPC programs funded by the U.S. **National Science Foundation (NSF)** and concerted efforts by universities. And while these efforts have produced valuable results and many insights on how to recruit and retain members of other historically marginalized groups in computing, none (to the best of our knowledge) have quantitatively examined how student identity moderates the efficacy of different interventions (especially for Black women), nor how interventions compare vis-à-vis each other.

Eleven alliances were established as part of the NSF BPC Alliances program by 2009, each one focusing on a particular part of the computing education pipeline or demographic group [18]. The **Alliance for the Advancement of African American Researchers in Computing (A4RC)** alliance was the singular alliance focused on improving participation for Black students, originally focused on establishing partnerships between **Historically Black College and University (HBCU)** with research universities to promote undergraduate research [18]. The newer **Institute for African American Mentoring in Computing Sciences (iAAMCS)** alliance now improves the experience of Black students in computer science by serving as a national resource and building mentoring relationships and networks. Their research identifies that Black women continue to be even more underrepresented than their male counterparts in postsecondary programs and in the faculty [29], indicating both that there is a significant need for role models, and this may be even more important for Black women, who are extremely underrepresented at the undergraduate level. Like the STARS program (from which we draw our data), iAAMCS promotes a number of interventions to improve the experience of Black undergraduate students in computing, including faculty and staff training, support to attend the Tapia Conference, technical webinars, robotics competitions, undergraduate research opportunities, and writing supports

[29]. The iAAMCS program has contributed significantly to the literature on the experiences of Black women in computing, particularly through their 2014 qualitative analysis of focus group interviews of 15 Black women who have been successfully engaged in computing programs [14]. This article employed Black Feminist Thought and Critical Race Feminism as a theoretical foundation, arguing that the intersectional experiences of Black women provide a unique viewpoint that are not the result of adding race to gender or vice versa. These foundations were played out in interview responses, with participants stating that it was impossible to tease apart their racial and gendered identities when trying to understand their experiences with faculty and peers in computing.

Universities have also been encouraging the broader participation of women, people with disabilities, and students from historically marginalized groups in their CS departments. The most prominent of these has focused on increased participation of women. For example, from 1995 to 2000, the CS department at Carnegie Mellon University conducted a longitudinal study that compared the perceptions, confidence, and interest in computing between women and men, and designed systemic changes to admissions, culture, pedagogy, curricula, support, social engagement, and staff to raise the percentage of women in the incoming class from 7% in 1995 to 42% in 2000 [32]. Similarly, efforts focused on achieving gender parity at Harvey Mudd College by addressing curriculum, pedagogy, culture, and applying a targeted strategy to appoint and promote women in leadership roles [2, 50] yielded a significant increase in the percentage of women computer science graduates from 15% in 2006 to 55% in 2016 [90].

However, such efforts have not conducted quantitative analyses of how these effects are moderated by race (likely due to the small number of non-white, non-Asian women); thus, one cannot conclude that these efforts were equally efficacious for Black women. Indeed, London and colleagues' [55] systematic review of BPC scholarship finds this dearth of intersectional evaluation studies to be a common problem in engineering and computer science. In particular, "...most evaluation studies report findings with respect to each gender. This is likely due to most interventions being either focused on race (e.g., people of color) or gender (e.g., girls), but seldom targeting those with an intersectional identity (e.g., girls of color)" [55, p. 234]. This is echoed by Ross et al. [82, p. 12], "The literature often groups Black women together with either Black/underrepresented groups or women, often omitting, disregarding, or overlooking the unique experiences situated at the intersection of race and gender."

1.3 The STARS Program as a Lens to Quantitatively Measure and Improve Black Experiences in Computing

The STARS program provides both an ideal setting and appropriate data to examine and improve the experiences of Black women in computing as it contains (1) variation in the ways that students engage in STARS program elements and their resulting experiences (providing necessary variation in the independent variable, which allows us to quantitatively examine which interventions are most predictive of intentions to persist in computing), and (2) a diverse student population with approximately equal numbers of white and Black students. We provide details of the variation in student experiences in this section (below) and a numeric breakdown of the student population in the next section on our data.

The STARS Computing Corps engages computing faculty and students at colleges, universities, and community colleges in a community of practice [25, 98] with a shared commitment to take action to advance diversity, equity, and inclusion in computing. The flagship activity for college and university students in the STARS program is the **STARS Leadership Corps (SLC)** program. From its inception in 2006 to 2017, the SLC has engaged over 2,100 college students and 300 faculty from 53 colleges and universities in service-learning projects. In these SLC projects, STARS faculty and students collaborate with local, regional, and national partners to apply inclusive practices to

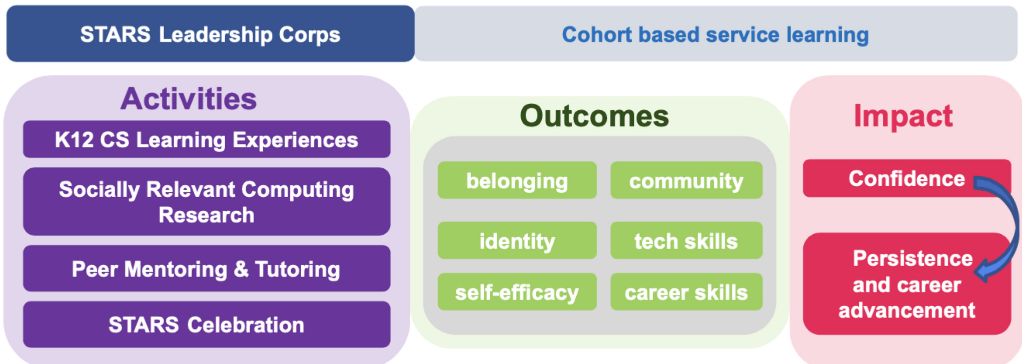

Fig. 1. The STARS leadership corps model.

Table 1. SLC Leadership Project Types

Project Types	*Example Projects*
K-12 Outreach	Middle School Robotics Club
	Boys & Girls Club Tri-IT Afterschool
Community Service	Tech installs for Habitat for Humanity
	BullyShutDown teaching tool for bully prevention
Tiered Mentoring	SLC Student to High School Student Mentoring
Peer Ambassador	CS1 Tutoring
	Women in Tech club
Research	Undergraduate research in socially relevant computing
	Research experiences for teachers collaborative

share their CS knowledge and broaden the participation of historically marginalized groups in computing in K-20. In addition to working with K-20 students, the SLC is a cohort-based model that encapsulates conference attendance, training, and BPC action as part of student-led, faculty-mentored teams.

All academic institutions joining STARS are expected to implement the SLC, and are provided with faculty training, resources, and a community to support student teams to develop and lead equitable and socially relevant projects using service-learning best practices [26, 72]. In sum, the STARS model creates a BPC community of practice [98] through tiered mentoring among faculty, graduate students, and undergraduate students (see Figure 1).

More specifically, SLC students undertake computing-focused leadership projects in their community, such as K-12 outreach, community service, tiered mentoring, peer ambassadors (college in-reach), and undergraduate research (see Table 1 for project types and example projects). Leadership projects are conducted during the academic year at their schools, with students committed to an average of 5 hours per week. All leadership projects include project planning and design, written reflection, presentation to peers, and outreach components.

STARS students are also encouraged to attend the STARS Celebration, a student-centered conference with sessions that provide technical and professional development relevant to persistence and advancement in computing, including sessions on career paths, graduate study and research opportunities, and mentoring in computing, as well as facilitated networking opportunities. The STARS Celebration conference welcomes new participants each year to orient them to the STARS program and connects students with other members of the STARS community. This has been found to be a particularly valuable experience for students from marginalized racial, ethnic, and gender groups. In addition, the STARS Celebration trains SLC cohorts to create and implement a BPC action plan (adapted to their local contexts and populations) and provides a venue for students and faculty to share new BPC practices, resources, and outcomes so that SLC cohorts can learn from each other. Such cohort-based opportunities for training and reflection have been found to be critical components for enhancing academic outcomes [8, 44, 73]. Importantly, the Celebration also provides opportunities for STARS students to learn more broadly about CS career opportunities, to collaborate with faculty, and to network professionally.

As part of the STARS community of practice, STARS institutions tailor the SLC intervention to fit their local needs and capabilities, while learning from other institutions. Since students engage in STARS in a multitude of ways, STARS students have a variety of experiences that can be scaffolded throughout their education. For instance, first- and second-year undergraduates may engage in outreach activities that increase awareness of computing careers for K-12 students while developing their own confidence and computing identity [72]. Upper-level undergraduates may engage in peer tutoring to promote entry-level student ability and persistence while serving as role models [71, 72]. There is variation in how closely students work with their faculty mentors or other students, whether students attend the STARS Celebration, the extent to which students engage their own technical expertise in their SLC projects, whether students conduct research, and the degree to which students to engage in socially relevant computing (among others). These variations enable students to have multifaceted experiences to fit their personal and academic contexts over time, while also providing a dataset that allows comparison of these variations for their impacts on persistence in computing.

2 METHOD

2.1 Dataset

We use data collected in an annual STARS program evaluation survey from undergraduate STARS participants. This survey was emailed to STARS participants at the end of each semester (i.e., in both the fall and spring), with questions about project engagement, attitudes about participating in the STARS program, and perceptions of how STARS participation impacted them socially, academically, and professionally. The survey instrument was designed from factors shown to attract and retain students in STEM fields. All items were assessed on a 6-point Likert scale.

2.2 Participants

The criteria for a survey response being included in the data analysis were that (1) the participant was an undergraduate student, (2) it was a student's first end-of-semester survey response, and (3) the student answered all 17 items included in the data analysis (see Table 2 for a list of survey items). This exclusion criterion was necessary to prevent overweighting the experiences of students who were heavily involved in STARS (as some students participated in the STARS program for years and took the survey numerous times) and to remove responses from graduate students and faculty. This left a sample of 814 students. Given that a total of 2,182 undergraduates participated in STARS during the time this survey was fielded (between Spring 2008 and Spring 2017), this constitutes a survey response rate of 37%.

These students were representative of the diversity of students involved in STARS, the range of institutions participating in STARS, and the engagement activities of the SLC. In total, students who completed the survey hailed from a wide range of 51 different institutions of higher education. While we did not have full demographic data on all of the 814 participants included in the final sample (as some students answered the questions needed for the data analysis without giving

Table 2. Means and Standard Deviations of Items

STARS Interventions	Mean	Std. Dev.
Increased my awareness of career opportunities	4.92	1.21
Made me feel more confident in my computing abilities	4.90	1.17
Allowed me to develop my computing skills and knowledge	4.91	1.17
Provided me with the chance to network professionally	4.83	1.24
Allowed me to help others understand the value of computing	5.13	1.05
Gave me more opportunities to work with people like me	5.13	1.11
Increased my collaboration with faculty	5.00	1.16
Increased my work with my peers	5.11	1.11
Helped improve my academic performance in my major	4.41	1.31
Was personally rewarding	5.20	1.05
Was demanding of my time	4.24	1.39
Improved my leadership skills	5.00	1.15
STARS Computing Persistence Construct – Individual Items		
Increased my interest in graduate education	4.71	1.31
Increased my commitment to my major	5.11	1.08
Increased my interest in computing research	4.77	1.22
Made me feel more committed to a career in computing	4.98	1.19
STARS computing persistence index	4.89	1.04

information), of the students that were included in the final sample that gave demographic data, about 49% identified as women, 38% identified as Black, 38% identified as non-Hispanic white, 9% as Asian, 8% as Hispanic, less than 1% as Native American, and 6% as another racial group. About 10% of survey respondents were first-year students, 22% sophomores, 32% juniors, and 35% seniors. About 27% of the population attended a HBCU and 2% attended an **Hispanic-serving Institution (HSI)**.

STARS participants were asked to select a primary activity as the focus of their effort in STARS and a secondary activity that would complement their primary activity and provide an opportunity to work with others. Students participated in a diverse array of primary and secondary STARS activities, including K-12 outreach, mentoring, peer ambassadors, outreach with members of the community (i.e., at nursing homes, with refugees, geek-a-thons, etc.), and internships (see Figure 2 for a detailed breakdown of students' primary and secondary STARS activities). Many students chose K-12 outreach as their primary activity (43.4%) and mentoring as a secondary activity (27.3%).

2.3 Measures

Aside from demographic data such as race, ethnicity, gender, institution type, and academic year, we collected data on participants' perceptions of STARS interventions (captured by the *STARS Interventions*) and participants' intentions to persist in computing (captured by the *Computing Persistence* construct).

STARS Interventions include 12 program evaluation items designed to measure students' perceptions of the STARS program interventions they experienced. These items capture a wide array of the ways that BPC programs can impact their students: for instance, through awareness of career opportunities, confidence, development of skills, network opportunities, and so on. All these items asked participants to respond along a 6-point Likert scale from 1 (Strongly Disagree) to 6 (Strongly

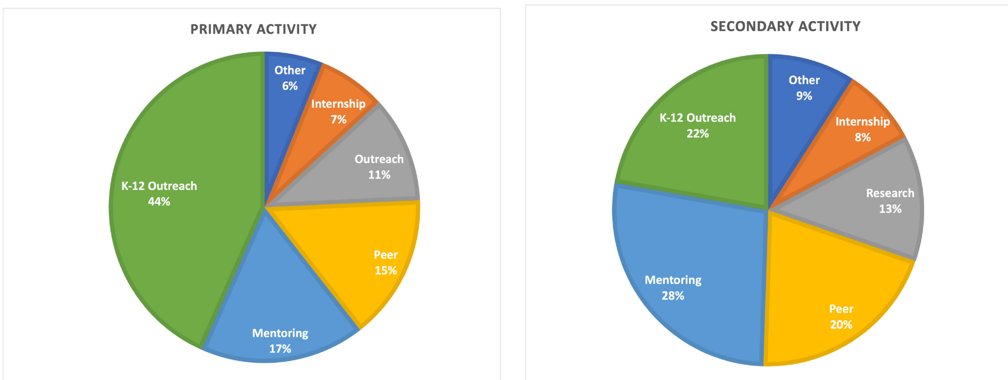

Fig. 2. Primary and secondary STARS activities.

Agree). Each item was used as an independent variable to analyze and compare their unique predictive power in the persistence of each group examined. Table 2 shows the STARS Interventions items, as well as the mean and standard deviation for each item. In general, students expressed high degrees of agreement with these items (see Table 2 for details).

The STARS Computing Persistence construct serves as an outcome variable that measures the impact of STARS participation on students' intentions to persist in computing. Specifically, the four items in the *STARS Computing Persistence* index were averaged to capture student perceptions about whether participating in STARS increased their interest in graduate education, commitment to their major, interest in computing research, and commitment to a career in computing. Each is measured on a 6-point Likert scale from 1 (Strongly Disagree) to 6 (Strongly Agree). This measure is akin to the persistence index used by Correll [23] and Fisk et al. [34], as it combines several operationalizations of persistence (i.e., persistence in major, graduate education, research, and career). This index had high alpha reliability ($\alpha = .89$) and indicated high levels of agreement that participating in STARS increased students' likelihood of persisting in computing, as the mean computing persistence index score was 4.89 out of a maximum possible score of 6 (SD = 1.04).

While we did not measure students' actual persistence by collecting data across academic institutions about individual students' degree completion, actual persistence in STEM fields has been found to be predicted by intentions to persist [60], and, "...hundreds of research efforts occurring [since the late 1960s] support the contention that intention is the 'best' predictor of future behavior" [60, p. 157]. In addition, recent work has found that intentions to persist in computing do predict enrollment in future computing courses [42].

2.4 Statistical Approach

We use linear regression in our analyses, which allows us to predict a given outcome variable (in our case, Computing Persistence) controlling for a multitude of independent variables (in our case, the 12 STARS Interventions items). This allows us to simultaneously estimate the relative importance of these different facets of the STARS program vis-à-vis each other. Regression coefficients can be interpreted as follows: The coefficient for a given independent variable indicates how much the outcome variable (i.e., persistence in computing) is expected to change when the independent variable increases by one unit (holding all other variables in the model constant). For instance, in Table 3, Model A, the coefficient for "Increased my awareness of career opportunities" is .21. This means that when career awareness increases by one unit, we would expect to see Computing Persistence increase by .21 units. Given that this is cross-sectional data,

Table 3. Linear Regression Analyses Predicting Students' Intentions to Persist in Computing by Group with Unstandardized Coefficients

STARS Interventions	Model A full sample	Model B Black women (all)	Model C Black men (all)	Model D white women (all)	Model E white men (all)
Increased my awareness of career opportunities	0.21 **	0.22 *	0.12	0.24 **	0.22 **
Made me feel more confident in my computing abilities	0.20 **	0.10	0.17	0.25 **	0.34 **
Allowed me to develop my computing skills and knowledge	0.16 **	0.14	0.18	0.08	0.06
Provided me with the chance to network professionally	0.09 **	0.17 +	0.30 **	-0.06	0.09
Allowed me to help others understand the value of computing	0.08 +	0.01	-0.03	0.19 *	0.12
Gave me more opportunities to work with people like me	0.08 +	-0.02	0.00	0.24 *	0.14
Increased my collaboration with faculty	0.07 *	0.18 *	0.07	0.03	0.07
Increased my work with my peers	-0.07	-0.17	0.00	0.05	-0.17
Helped improve my academic performance in my major	0.06 *	0.06	0.03	0.05	0.04
Was personally rewarding	0.02	0.20	-0.03	0.07	-0.15
Was demanding of my time	0.01	0.04	0.06	0.04	-0.04
Improved my leadership skills	0.00	-0.03	0.05	-0.16	0.16
Intercept	0.43 **	0.55	0.54 +	-0.25	0.52
n	814	142	166	156	152
r^2	0.76	0.77	0.80	0.81	0.79
adj r^2	0.76	0.75	0.78	0.79	0.77

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.10$. NOTE: Bonferroni p-value correction was applied, wherein we multiply a coefficient's predicted p value by the number of tests performed (in this case, by a factor of 12, since there are 12 independent variables).

our analyses cannot make causal claims about the impact of a given independent variable on the dependent variable. However, these analyses elucidate relationships between our variables of interest, a crucial first step in assessing causality.

In our analysis, we use a Bonferroni p-value correction, wherein we multiply a coefficient's predicted p-value by the number of tests performed (in this case, by a factor of 12, since there are 12 independent variables). We perform this correction to reduce the likelihood of false positives, as we did not have strong hypotheses about the relative effects of the different STARS interventions. We also present the results of regression analysis with both unstandardized coefficients (Table 3) and coefficients that have been adjusted to reflect their relative effect size (Table 4), given that many readers are more familiar with effect sizes than unstandardized coefficients. Thus, the coefficients in Table 4 can be interpreted as effect sizes: For instance, the effect size for "Increased my awareness of career opportunities" is 0.09 in Table 4, Model A. That means that "Increased my awareness of career opportunities" has a small impact on computing persistence intentions, as Cohen suggests that small, medium, and large effect sizes are 0.10, 0.30, and 0.50, respectively [19].

3 RESULTS

3.1 Overview of Regression Analyses

In Table 3 (with unstandardized coefficients) and Table 4 (with effect sizes), we predict Computing Persistence intentions using the 12 STARS Interventions items. Model A includes all students (n = 814), Model B includes only Black women (n = 142), Model C includes only Black men (n = 166), Model D includes only white women (n = 156), and Model E includes only white men (n = 152). It is worth noting that none of the individual interventions have large effect sizes on

Table 4. Linear Regression Analyses Predicting Students' Intentions to Persist in Computing by Group with Effect Sizes

STARS Interventions	Model A full sample		Model B Black women (all)		Model C Black men (all)		Model D white women (all)		Model E white men (all)	
Increased my awareness of career opportunities	0.09	**	0.07	*	0.03		0.10	**	0.13	**
Made me feel more confident in my computing abilities	0.05	**	0.01		0.03		0.09	**	0.13	**
Allowed me to develop my computing skills and knowledge	0.03	**	0.02		0.04		0.01		0.00	
Provided me with the chance to network professionally	0.02	**	0.05	+	0.17	**	0.01		0.03	
Allowed me to help others understand the value of computing	0.01	+	0.00		0.00		0.06	*	0.03	
Gave me more opportunities to work with people like me	0.01	+	0.00		0.00		0.08	*	0.04	
Increased my collaboration with faculty	0.01	*	0.07	*	0.01		0.00		0.02	
Increased my work with my peers	0.01		0.04		0.00		0.00		0.04	
Helped improve my academic performance in my major	0.01	*	0.01		0.00		0.01		0.00	
Was personally rewarding	0.00		0.03		0.00		0.00		0.04	
Was demanding of my time	0.00		0.01		0.02		0.01		0.01	
Improved my leadership skills	0.00		0.00		0.01		0.03		0.05	

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.10$ NOTE: Bonferroni p-value correction was applied, wherein we multiply a coefficient's predicted p value by the number of tests performed (in this case, by a factor of 12, since there are 12 independent variables).

Computing Persistence (i.e., all coefficients in Table 4 are less than or equal to .17). However, it appears that these small effects add up, as these models are generally quite predictive: all models have adjusted r^2 values in the .75 to .79 range, meaning that between 75% and 79% of the variation in Computing Persistence is explained by the STARS Interventions items. Given the possibility of multicollinearity in the data, we also checked the variance inflation factor (VIF) values for all the regressions. The vast majority of VIF values were under 5, and all VIF values were under 10, indicating acceptable levels of multicollinearity, as 10 is a common VIF cutoff threshold [40].

The presentation of data in Tables 3 and 4 allows for a detailed comparison of effects that occur for the full sample versus by demographic group. Table 5 presents a summary of statistically significant effects for each group. While we are primarily focused on the effects of interventions on Black women, we first detail results for the overall sample (Model A in Tables 3 and 4) as a comparison point. We then present results broken down by the following demographic groups: Black women, Black men, white women, and white men (in Models B–E, respectively). This allows us to compare effects, and to draw attention to how student identity moderates the effects of interventions. For instance, a 1-unit increase in confidence is correlated with a .20-point increase in Computing Persistence for students in the full sample ($p < 0.01$, Table 3, Model A). However, this varies significantly by a student's race and gender identity. A 1-unit increase in improved confidence is correlated with a .10-point increase in the computing persistence intentions of Black women (N/S, Table 3, Model B), a .17-point increase in the computing persistence intentions of Black men (N/S, Table 3, Model C), a .25-point increase in the computing persistence intentions of white women ($p < 0.01$, Table 3, Model D), and a .34-point increase in the computing persistence intentions of white men ($p < 0.01$, Table 3, Model E). So, while improving confidence is associated with increased persistence for the full sample of STARS students, its effects are not uniformly distributed: Although we have evidence that improving confidence is associated with increased persistence for some students (i.e., white women and men), there is no statistically significant evidence that

Table 5. Statistically Significant Predictors of Intentions to Persist in Computing by Group

full sample	Black women	Black men	white women	white men
Increased my awareness of career opportunities	Increased my awareness of career opportunities	Provided me with the chance to network professionally	Made me feel more confident in my computing abilities	Made me feel more confident in my computing abilities
Made me feel more confident in my computing abilities	Increased my collaboration with faculty		Increased my awareness of career opportunities	Increased my awareness of career opportunities
Allowed me to develop my computing skills and knowledge			Gave me more opportunities to work with people like me	
Provided me with the chance to network professionally			Allowed me to help others understand the value of computing	
Increased my collaboration with faculty				
Helped improve my academic performance in my major				

improving confidence in computing abilities is associated with the persistence intentions of Black women and men.

Unfortunately, our small sample sizes of students from other demographic groups (e.g., Hispanic men, Asian women) limited our ability to conduct robust statistical analyses on their experiences in computing; thus, we do not present separate regressions for these groups of students. Future analyses should investigate their experiences in more detail.

3.2 Full Sample and Interventions for Computing Persistence

In the overall pool of STARS students, we find that six interventions have a statistically significant relationship with computing persistence (ranked from largest to smallest effect size):

(1) Increased my awareness of career opportunities (effect size = .09)
(2) Made me feel more confident in my computing abilities (effect size = .05)
(3) Allowed me to develop my computing skills and knowledge (effect size = .03)
(4) Provided me with the chance to network professionally (effect size = .02)
(5) Increased my collaboration with faculty (effect size = .01)
(6) Helped improve my academic performance in my major (effect size = .01)

The relative magnitude of these effect sizes suggests that while improving computing ability predicts persistence in computing (as both, “Allowed me to develop my computing skills and knowledge" and "Helped improve my academic performance in my major" were statistically significant predictors of persistence), they are not the most predictive interventions. Instead, we see that career awareness has the largest positive association with persistence in computing, followed by the socio-emotional factor of developing confidence in computing abilities. This suggests that simply educating students on the wide variety of careers in computing and increasing their confidence in their abilities are important facets of increasing persistence in computing. In addition, we find that professional relationships are quite important to students' persistence, as "Provided me with the chance to network professionally" and "Increased my collaboration with faculty" are statistically significant predictors of computing persistence.

Interestingly, none of the following items were predictive of computing persistence for any demographic group: "Increased my work with my peers," "Was personally rewarding," "Was demanding of my time," and "Improved my leadership skills." This does not necessarily mean that these items have no effect on computing persistence, simply that we do not have statistical evidence that they have an association with computing persistence intentions once we control for other types of interventions.

We next examine how these effects vary by students' race and gender identity. This allows us to assess which interventions are most predictive of Black women's computing persistence intentions, and how this compares to other students. The reader will note that the following results section is rather short, consisting of a listing of which interventions were and were not predictive for different groups of students. Given that we rely on other research to interpret these effects (as opposed to using our own data), and that we draw comparisons across groups to make larger points, we present most of our analyses in the discussion.

3.3 Black Women and Interventions for Computing Persistence

For Black women, *career awareness* (effect size = .07) and *faculty mentorship* (specifically, by increasing *collaboration with faculty members*, effect size = .07) were the only interventions that statistically predicted their computing persistence intentions. Networking (effect size = .05) had a marginally significant association with intentions to persist but was not significant at the $p < 0.05$ level.

Confidence and building computing skills/knowledge *did not* have a statistically significant association with Black women's intentions to persist in computing. Moreover, their estimated effect sizes were close to 0, suggesting that the lack of effect is not simply due to a lack of statistical power.

3.4 Black Men and Interventions for Computing Persistence

For Black men, *professional networking* was the only intervention that had a statistically significant association with their computing persistence intentions, and it had a positive association of medium effect size (.17). Confidence, career awareness, and perceived computing ability *did not* have a statistical association with Black men's intentions to persist in computing.

3.5 White Women and Interventions for Computing Persistence

For white women, *career awareness* (effect size = .10), socio-emotional factors (i.e., confidence in abilities [effect size = .09], allowed me to *help others understand* the value of computing [effect size = .06]), and *peer collaboration* (i.e., gave me more opportunities to work with people like me [effect size = .08]) were the only interventions that predicted computing persistence intentions. Perceived computing ability *did not* have a statistically significant association with white women's intentions to persist in computing.

3.6 White Men and Interventions for Computing Persistence

For white men, *confidence* (effect size = .13) and *career awareness* (effect size = .13) predicted computing persistence. This might appear to be quite unexpected, as white men are more integrated in the field of computing than the aforementioned groups of students (and thus we would expect that they would be most aware of career opportunities) [30] and are stereotyped as having an abundance of confidence on male-typed tasks like computing [75]. However, since these are results from regression analysis (versus the presentation of summary statistics), these results simply state that confidence and career awareness are important predictors of white men's persistence intentions in computing, independent of their starting values.

4 DISCUSSION

What broader conclusions can we draw from these results? Based on the extant literature and comparisons across groups, we believe that there are four important takeaways from these analyses, which we detail below.

4.1 Interventions to Increase the Persistence of Black Women in Computing

Given the numerical dearth of Black women in computing, most samples of computing students typically do not have enough Black women in them to produce statistically meaningful analyses. Thus, these results are the first (to our knowledge) to quantitatively assess how different types of interventions predict Black women's persistence in computing.

We find that *career awareness and faculty mentorship* are the two interventions that have a statistically significant, positive relationship with Black women's computing persistence intentions. This does not mean that all other interventions are unimportant; instead, this means that we did not find evidence for the efficacy of other interventions on Black women. These results are echoed in other work on the experiences of Black women in STEM and computing; for instance, a study on Spelman College (an all-woman HBCU with a high rate of STEM graduates) found evidence for the importance of high faculty contact, active engagement of faculty in student success, cooperative peer culture, academic supports, and undergraduate research [76].

We suspect that career awareness is especially important for Black women because of the ways that careers are transmitted through families in conjunction with the racial and gender segregation of the labor market. The labor market remains incredibly segregated by race and gender, so that Black women have very different jobs than Black men, white women, or white men [105]. Black women are even more proportionally underrepresented in computing than Black men: For instance, Black women and men make up about 14% of the U.S. population [10] but make up only 6.8% of computer and information systems managers, of which 4.5% are Black men but only 2.3% are Black women. This means that Black women are particularly unlikely to have careers in computing transmitted to them by their parents, because careers are largely transmitted through parents in a gendered fashion; namely, fathers disproportionately pass on male-typed occupations to their sons compared to daughters [106]. Thus, making Black women aware of the types of careers that can flow from a degree in computing may be particularly important for their persistence, as they are less likely to obtain this information at home.

We also found that faculty mentorship was predictive of Black women's persistence intentions in a way that it was not for any other group of students we examined (Black men, white women, white men). We suspect that mentorship is particularly valuable to Black women's persistence in computing due to the extreme numeric rarity of Black women in computing, the small range of "acceptable" or "respectable" behaviors Black women can display in computing due to gendered racism [88], and the frequency of feeling excluded and isolated by peers [15, 80]. Mentorship likely gives Black women tools to navigate these disadvantageous spaces; for instance, information about dress codes, language (code-switching), access to resources and networking groups, and so on [69], as well as relational and emotional support. And indeed, other research that has more formally studied Black women's faculty mentorship highlights its importance, finding that Black faculty mentorship creates a unique space and refuge from systems and experiences of racial oppression that persist in the academy for Black women. Women of color in STEM have even found mentorship to act as a counterspace in which they feel supported by mentors of color who understand their unique intersectional difficulties and know the resources they need to persist [68]. They describe such support systems as, "...the most valuable tool for success in a STEM graduate program," and the factor that makes everything seem less intimidating [99, p. 57]. Moreover, the relationship between Black women faculty and Black women students is particularly valuable, as Black women faculty personally understand the marginalization Black women face in educational and professional settings [28, 59, 100] while still being able to see their Black women students beyond the race/gender binary, through a lens respecting the complexity of the whole person. Lastly, Black women can visualize the manifestation of persistence in computing through Black women faculty, and experience unique relational ties in a space that was not built for them in mind, the academy [70]. For these reasons, consistent support and being held accountable to faculty mentors is a major factor in helping Black women doctoral students complete their degrees [45].

Finally, we suspect that building confidence might not be as important for Black women's computing persistence simply because Black women likely must be extremely confident in their skills to even consider pursuing a career in computing, given the extensive barriers they face in this field. See Section 4.3 (below) for more details on this phenomenon.

4.2 Black Women's Needs Are Often Neglected in Broadening Participation Efforts

While many researchers, educators, and advocates have recognized that Black women's needs are often overlooked by efforts to diversify computing, this analysis provides quantitative support for this argument. Frequently, this neglect is the result of studies that employ poor measurements and analyses of identities (especially in regard to intersectionality), leading to poor understandings of how gender, race, socioeconomic status, nationality, and so on, influence computing experiences [61]. For instance, efforts to diversity computing will focus on "women" or "underrepresented racial groups" and assume that these efforts will meet Black women's needs, because these groupings technically include Black women. Similar processes occur in statistical analyses, which often use models in which Black women are lumped in with women of all other races. But since the samples of women used in these analyses are typically disproportionately full of white women, these statistical analyses that report on the needs of "women" are actually reporting the needs of white women. This same phenomenon can also occur when researchers study "Black students" in computing, given that Black women are also numerically rarer than Black men in samples of computing students. This is problematic, because Black women face barriers not only because they are Black and a woman but also because of the unique intersecting systems of oppression working against Black women.

More specifically, many calls-to-action to increase the number of women in computing revolve around socio-emotional interventions like building confidence (e.g., Reference [93]), working with others, and expressing creativity (e.g., Reference [84]). For instance, the **American Association of University Women (AAUW)** states that one way to get more women into tech and engineering is to, "Spread the word that engineering and computing fields have enormous social impact. Women, on average, prioritize 'communal goals' in their careers, meaning that they value working with and helping people" [6]. And **National Center for Women & Information Technology (NCWIT)** mentions, "Decreased confidence among women is a frequently recurring theme in STEM and IT research. Women are more likely than men to lose confidence in their ability to complete the tasks required for earning acceptable grades, even when their performance is equal to males," when explaining how to retain women through inclusive pedagogy [4, p. 1]. Underpinning this phenomenon is the fact that interventions designed for "women in computing" are often focused on psycho-social, emotional factors tied to expectations of women and stereotypes of femininity, like the ones we found to be significant predictors of white women's computing persistence (i.e., confidence, working with others like themselves, and allowing others to understand the value of computing). However, since gendered expectations for women are typically tied to stereotypes of femininity, and such stereotypes are based on middle-class white women [33], interventions based on gendered expectations and stereotypes are less likely to be useful to Black women.

And indeed, when we broke Black women and white women into separate analytical categories, we found that building confidence and working with "people like me" through STARS was a predictor of computing persistence intentions for white women but not Black women. Given that gender-focused efforts to diversify computing more closely resemble our list of significant predictors of persistence for white women than Black women (e.g., Reference [65]), this suggests that efforts to bring more "women" into computing have indeed been largely focused on bringing more white women into the field. While this is far from the first time that such a claim has been made [55, 63, 82], few studies have presented quantitative evidence for this claim.

To be sure, some needs are shared by Black and white women. For instance, our analysis reveals that awareness of career opportunities was predictive of persistence for Black and white women (and white men). But if Black women's intersectional experiences continue to be ignored, then effective solutions to meet Black women's needs will remain out of reach [57].

4.3 Interventions to Increase the Persistence of Black Students in Computing

While this article is focused on Black women, we did feel it was worth mentioning commonalities between Black women and Black men. We do this for two reasons. First, the fact that Black women's needs overlap more with Black men than white women tells us something important about Black women's experiences in computing, namely, that structural and social processes around race may be more disadvantageous to Black women than social processes around gender. Second, these findings may be useful for practitioners who are broadly interested in increasing racial diversity in computing.

We found two general trends about Black versus white students' needs in computing, regardless of student gender. First, interventions focused on building connections with others were more connected to persistence for Black students than white students; in particular, networking had a strong positive relationship with persistence for Black men and a marginally significant effect for Black women, and faculty mentorship was an important predictor of persistence for Black women. But networking and faculty mentorship were not associated with white women's or men's computing persistence. Second, building confidence was an important predictor for persistence for both white women and men, but was not a statistically significant predictor for Black women or men. Why might this be the case?

We suspect that because Black people are so numerically underrepresented and systematically excluded in computing education and computing careers [29, 82, 107], connections with others are especially important for their persistence, as such ties may increase their feelings of belonging within the field [47], facilitate the transfer of informal knowledge about careers in computing [1], and provide them with important mentorship opportunities [36, 41, 76] that build social capital [62]. And indeed, research finds that Black computing students have better educational outcomes when they have access to strong networks within their educational settings that provide them with these forms of knowledge, support, and resources, like those experienced in programs like STARS, iAAMCS [97], and African American Researchers in Computing Sciences [16]. We surmise that network ties are less important for white students' persistence, given that white students—even white women—are much less likely than Black students to be "the only" in computing spaces.

We also suspect that confidence is less important to Black students' than white students' computing persistence because of the greater barriers Black students face in pursuing computing. As mentioned in the literature review, Black students are structurally much less likely to be exposed to computing before college (due to the racially segregated nature of education in America) and then face interactional barriers (including racialized and gendered hostility) if they pursue a computing degree in college. Thus, we suspect that Black students must be extremely confident in their computing abilities to make it into the STARS program. And indeed, students of color in STEM graduate programs have described deriving motivation from recognizing the fortitude they needed to get to where they are "The doubts of others about your strengths and your abilities, both academic and otherwise, may pile on top of the doubts that you may have about yourself. But you did NOT get here by accident. You are smart, you are strong, and you are capable" [99, p. 58]. Students facing constant exclusion, hostility, lack of support, and similar barriers might be driven out by such experiences if they were not incredibly driven and confident in their abilities to persist.

4.4 General Takeaways for Efforts to Diversify Computing

While the primary goal of this article was quantitatively interrogating which interventions were most important for increasing Black women's persistence in computing, these analyses led us to three general conclusions about efforts to diversify computing that we felt were worth sharing. First, the interventions that retain students in computing (i.e., those who have already shown an interest in computing) are likely different than the types of interventions that are needed to catalyze student interest in computing. These analyses were focused on keeping students in computing, which is important given that many students who show an interest in computing end up leaving the field [5, 49]. However, given the dearth of Black women who even take a computing course in college, greater efforts are needed before college to get Black girls interested in computing. Our analyses suggest that students' intersectional identities will also influence what approaches are best for getting them interested in computing.

Second, we found that career awareness was a predictor of computing persistence intentions for all students except Black men. Career awareness and preparation typically begin well before reaching college, as computing students tend to report early exposure to and fascination with technology at home and school [95], and they are more likely to persist in computing if they have parents in computing [31, 52, 84]. Most people learn about career opportunities through their parents and their surrounding communities. Indeed, computer programmers have parents who are computer programmers at a rate 6 times the rest of the population, a rate higher than most jobs [9]. This means that students who come from families with jobs in computing—families that are disproportionately white, Asian, and middle-upper class—are much more likely to be familiar with computing as a career option than other groups of students (e.g., Black and Hispanic students, middle and lower-class students, etc.). Thus, expanding students' awareness of the possibilities of a computing degree is an important way to increase students' persistence in computing.

Third, these results suggest that focusing on improving leadership, the personal rewards associated with computing, and peer work may not increase the persistence intentions of students who have already indicated an interest in computing. Future research is needed to understand these effects more fully.

5 LIMITATIONS AND GENERALIZABILITY

This study has several important limitations. First, these results examine which factors are associated with retaining students who are already interested in computing: They do not explore which interventions are most effective at attracting students to the field of computing. It is likely that what attracts students to the field of computing is different than what retains them in the field, and so different interventions may be necessary to attract Black women to the field of computing. This is supported by research findings that show that Black women who pursue careers in computing have attested to the influence of exposure and encouragement to learn computing from childhood [14]. This includes at-home opportunities to use and tinker with electronics and encouragement from family and friends to get into computing classes and activities [13, 78, 102].

Second, these are exploratory rather than confirmatory results. In other words, while these analyses are an important first step at quantitatively measuring how various interventions are predictive of Black women's intentions to persist in computing (as well as other demographic groups), they are a jumping-off point versus a directive on which interventions should, and should not, be used. For instance, just because we did not find evidence for the efficacy of a given intervention does not necessarily mean that it is a useless intervention for recruiting: It is certainly possible that our sample of students (i.e., students who got involved with the STARS program) are systematically different than other students in the field of computing. In addition, these are cross-sectional analyses that illustrate relationships between variables as opposed to causal effects.

Third, we were limited in our ability to conduct truly intersectional analyses as we did not examine how the effects of these interventions on Black women were moderated by institutional context (specifically, whether they attended an HBCU versus a **Primarily White Institution (PWI)**) or other aspects of their identities (i.e., social class, disability status, and sexuality). Black women at PWIs face different barriers than Black women at HBCUs (e.g., Reference [79]), and thus it is likely that institutional context mediates some of these effects. More specifically, we expect that Black women face much more racism at PWIs and may need even greater social support to persist in the face of such hostility. In addition, faculty mentorship may be more difficult to find for Black women in PWIs versus HBCUs. Future research should examine these issues in more detail. Moreover, to conserve statistical power, we were forced to collapse all Black women into a single category despite the ethnic and cultural diversity that exists (e.g., African, Caribbean, and Afro-Latina) as well as the plurality of Black women's lived experiences in the U.S. at the intersection of their identities like sexuality, religion, disability, first-gen status, socioeconomic status, and so on. Future research should interrogate how the intersection of these different identities impacts the efficacy of interventions to retain Black women in computing.

Fourth, our sample places important limits on the conclusions we can draw from our results. While the sample is diverse, it is likely not representative of all students with an interest in computing, as we used respondents who had participated in the STARS program. In addition, our sample may not represent the perspective of the entire STARS population of students, as there is likely a non-response bias from the students who did not complete the end-of-semester surveys. Our analysis was also focused on the effects of interventions after a single semester in STARS: It is also possible the effects would be different with longitudinal data. In addition, there is a self-selection bias of STARS students who remained in the program until the end of the semester.

Fifth, this analysis is of attitudinal data. In other words, we have examined how student perceptions of the efficacy of various STARS interventions predict their persistence intentions. While research has found that students' intentions to persist in computing are predictive of their actual persistence [42], future research should examine how interventions impact Black women's actual persistence in computing.

And finally, we were only able to examine a limited number of interventions (i.e., those included as STARS Interventions items), as opposed to the entire universe of possible interventions to diversify computing. Future research should replicate this approach using different types of interventions.

5.1 Implications and Final Conclusions

Black women in computing need interventions that are tailored to meet their specific needs. Unfortunately, due to limited sample sizes and effort, there has often been an underlying assumption that what works for students from other historically marginalized groups in computing (in particular, white women and Black men) will work for Black women. While qualitative research about Black women in computing has made this point, there have been few research studies that have quantitatively disentangled the effects of different interventions on students' intentions to persist in computing, examining how a student's identity moderates these effects. Using unique data, with both a large-enough sample of Black women for statistically meaningful quantitative analysis and variation in interventions, we find that what is most predictive of Black women's persistence in computing (i.e., increasing career awareness and their collaborations with faculty) is both distinct and overlapping with the needs of students from other demographic groups. We hope that future research will build on these findings to craft computing experiences that best meet the needs of Black women.

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