Multi-Pronged Pedagogical Approaches to Broaden Participation in Computing and Increase Students' Computing Persistence: A Robustness Analysis of the STARS Computing Corps' Impact on Students' Intentions to Persist in Computing

Lauren Gabrielle Wyatt
lwyatt4@kent.edu
Kent State University
Kent, Ohio
USA

Susan Rebecca Fisk
sfisk@kent.edu
Kent State University
Kent, Ohio
USA

Clarissa Thompson
cthomp77@kent.edu
Kent State University
Kent, Ohio
USA

Jamie Payton
payton@temple.edu
Temple University
Philadelphia, Pennsylvania
USA

Veronica Cateté
vmcatete@ncsu.edu
North Carolina State University
Raleigh, North Carolina
USA

Audrey Rorrer
audrey.rorrer@uncc.edu
University of North Carolina
Charlotte, North Carolina
USA

Tiffany Barnes
tmbarnes@ncsu.edu
North Carolina State University
Raleigh, North Carolina
USA

Tom McKlin
tom@thefindingsgroup.org
The Findings Group
Atlanta, Georgia
USA

ABSTRACT

Multi-pronged programs that involve students in a combination of proven interventions (i.e., tutoring other students, building community, developing skills, etc.) constitute one pedagogical approach to increasing the number and diversity of computing professionals. In this manuscript, we evaluate the efficacy of one such multi-pronged program, the STARS Computing Corps, a Broadening Participation in Computing Alliance program funded by the National Science Foundation. These analyses improve upon previous efforts to assess the efficacy of STARS by examining dosage effects of the program, adding controls for students' initial intentions to pursue computing, and conducting these analyses at various points in a student's participation in STARS. We also conduct analyses to determine the efficacy of various STARS activities. Controlling for students' initial intentions to persist in computing, we find robust evidence that spending more time each week on STARS' activities positively predicts students' intentions to persist in a computing career, and that STARS has a heightened positive impact on Black and Hispanic students. We do not find evidence that the number of semesters a student spends in STARS is predictive of computing persistence, nor do we find differences in the efficacy of various STARS activities. In sum, these results suggest that STARS has a positive impact on students' intentions to persist in computing and that multi-pronged programs like STARS should focus on the intensity of participation (as opposed to the length of participation or a particular activity) to increase students' desire to persist in computing careers.

CCS CONCEPTS

• **Social and professional topics** → **Computer science education**; **Computing education**.

KEYWORDS

Broadening Participation in Computing, STARS Computing Corps, Evaluation of Pedagogical Approaches, Computing Persistence

ACM Reference Format:
Lauren Gabrielle Wyatt, Susan Rebecca Fisk, Clarissa Thompson, Jamie Payton, Veronica Cateté, Audrey Rorrer, Tiffany Barnes, and Tom McKlin. 2024. Multi-Pronged Pedagogical Approaches to Broaden Participation in Computing and Increase Students' Computing Persistence: A Robustness Analysis of the STARS Computing Corps' Impact on Students' Intentions to Persist in Computing. In *Proceedings of the 55th ACM Technical Symposium on Computer Science Education V. 1 (SIGCSE 2024), March 20–23, 2024, Portland, OR, USA.* ACM, New York, NY, USA, 7 pages. https://doi.org/10.1145/3626252.3630895

SIGCSE 2024, March 20–23, 2024, Portland, OR, USA.

ACM ISBN 979-8-4007-0423-9/24/03…$15.00
https://doi.org/10.1145/3626252.3630895

1 INTRODUCTION

Despite the need for highly educated people to enter the field of computing, there are still difficulties in recruiting and retaining new professionals in the field, especially among individuals from historically marginalized gender and/ or racial groups. To fill the need for computing professionals, a variety of approaches have been studied and adopted, including community-based service learning [33] and near-peer mentoring [13, 21]. One pedagogical approach has been to create multi-pronged programs that engage students in a combination of proven interventions (i.e., tutoring other students, building community, developing skills, etc.) in hopes of attracting and retaining students in the field of computing. A longstanding and well-known example using such an approach is the STARS Computing Corps, a Broadening Participation in Computing Alliance (BPC-A) program funded by the United States' National Science Foundation (NSF). The STARS Computing Corps, initiated in 2006, is a U.S. national organization with an alliance of over 40 institutions of higher education [8], which aims to, "...increase computing persistence and promote career advancement for undergraduates, graduate students, and faculty, with a focus on addressing systemic and social barriers faced by those from underrepresented groups in computing" [7]. In particular, STARS uses a multi-pronged approach to engage university students in leadership and professional activities including conducting research, hosting K-12 outreach, and networking with industry. Although each STARS chapter varies in its primary activities and resources available, an example cohort may have a graduate student lead curriculum development and community relations for a team of undergraduates wanting to host monthly workshops for middle school students. Another example may involve faculty mentoring early scholars in research activities.

Despite the prevalence of multi-pronged pedagogical approaches (such as STARS) to increase the number of computing professionals, efforts to assess the efficacy of these programs (and in particular, the STARS program) have been limited. For instance, many BPC programs have not allocated enough of their resources and funding toward evaluating the impact of their programs, especially on a longitudinal scale [31].

In this manuscript, we address this gap in the literature and more rigorously examine the efficacy of STARS by: 1) using computing persistence intentions as our dependent variable, and 2) conducting a series of analyses to ensure the robustness of our results. Firstly, we conduct analyses that directly examine the impact of STARS participation on computing persistence intentions, as opposed to using measures that are correlated with persistence, but are indirect measures of persistence (e.g., enjoyment, sense of community, satisfaction with major, changed attitudes toward computer science, etc.). As we were unable to measure students' long-term behavioral outcomes (i.e., pursuit of a career in computing), we instead use an attitudinal measure of intentions to persist in computing. While attitudinal measures are often overlooked in computing education research, it is widely accepted in social science research that intentions are predictive of behavior [19]. Indeed, research finds that intentions are predictive of behavior within STEM [24, 26], as well as the field of computing [16].

Secondly, we conduct a series of robustness checks including: examining dosage effects of the program (i.e., hours per week, number of semesters engaging in STARS), adding controls for students' initial intentions to pursue computing, and conducting these analyses at various points during a students' participation in STARS. We also conduct analyses to determine the efficacy of various STARS activities. While none of these analyses can establish a definite causal relationship between participating in STARS and computing persistence, they do allow us to present stronger claims about the efficacy of the STARS program in several ways. Firstly, if we find that STARS has a positive effect on computing persistence intentions, even when we control for students' initial intentions to persist in computing, we can rule out the alternative explanation that students who are motivated enough to join the STARS program have a greater affinity for computing and thus a heightened desire to persist in it. Secondly, examining dosage effects of STARS adds robustness to our conclusions by directly testing the assumption underlying the positive effects of STARS: namely, that if STARS increases students' desire to persist in computing, more time in STARS should have greater positive impacts on students. And finally, examining the relationship between STARS participation and persistence intentions at various time points throughout a student's tenure with STARS allows us to better understand the conditions under which an association holds.

2 FORCES THAT DECREASE PARTICIPATION IN COMPUTING

Despite a societal need for more computing professionals, there are many forces–both subtle and blatant–that discourage students from persisting in computing. These effects tend to be largest among students from marginalized gender and/ or racial groups. Many students of all genders and races drop out of introductory computing courses; for instance, it is estimated that 40% of students who enter computing degree programs drop out at some point, with the majority of the drop-off being within the first two years [14, 17]. There are many contributors to these high overall drop-out rates, including high DFW rates (i.e., receiving a grade of D, F, or Withdrawing from a course), difficulty of learning to program, inadequate advising, high demands on the student [14], etc. In addition, students from minoritized racial and gender groups are often discouraged from pursuing computing careers through a host of implicit and structural biases [20]. For instance, students from marginalized gender and/ or racial groups are more likely than their White male peers to leave their computing programs before graduation due to feeling isolated, overlooked, and oppressed [15, 32]. The exclusion and ostracization of marginalized students from computing is a key contributor to many marginalized students prematurely leaving their computing programs [25, 30]. It also serves to maintain the homogeneity of the field, leaves jobs unfilled, limits the innovation and growth of the computing field, and aids in maintaining social inequalities [22].

3 THE STARS APPROACH

In order to combat these forces that decrease participation in computing, the NSF funds organizations and programs focused on increasing participation in computing, especially among people from marginalized gender and/ or racial groups [2]. One of several original Broadening Participation in Computing Alliances funded by the NSF, STARS operates as an umbrella organization to help implement best practices identified across the field into strategic diversity, equity, and inclusion projects. At the annual STARS Celebration conference [11], university students and faculty learn about research and outreach best practices identified by other STARS members as well as sibling alliance organizations (i.e., the National

Center for Women in Computing, Access Computing, and the Institute for African-American Mentoring in Computing Sciences). Together with their university cohort, STARS students use this time at the Celebration to plan upcoming events and support structures for the following school year. Schools such as Florida State University have focused on programs that bring in industry professionals and entrepreneurs to speak with students about how to start their own companies. Programs like UNC Charlotte's help their STARS students mentor teachers and kids in K-12 classrooms as they learn computing. STARS at NC State University helps connect new undergraduate students from historically marginalized gender and racial backgrounds (e.g., women, Black, and Hispanic students) with research projects run by graduate student mentors. In every variation, the STARS program presents students with the opportunity to build participants' social community, skills, and confidence in computing, which are all factors that are essential to helping students feel invested in the field [9, 28].

4 PREVIOUS EFFORTS TO EVALUATE STARS

Previous research on the efficacy of STARS has yielded several promising results. For instance, studies conducted among multiple institutions have demonstrated that students who engage in STARS generally show improved GPAs, greater retention in their field of study, and increased commitment to their major [11, 27, 28]. Similarly, studies found that students who participate in STARS are more likely to see computing as a part of their identity and to feel more committed to computing than students who did not participate in STARS [3, 4, 10]. However, previous attempts to evaluate STARS have been limited in many ways, in large part due to a limited evaluation budget [31]. Firstly, previous attempts to evaluate the efficacy of STARS have primarily focused on evaluating specific aspects of STARS [6, 27, 29], as opposed to examining the overall impacts of STARS participation on the key variable of interest: computing persistence. Secondly, previous STARS evaluations have been limited by their small sample sizes, often focusing on a year or two of student data at a time. Thirdly, due to these small sample sizes and a lack of linkage between surveys, previous STARS analyses have been limited in their ability to use more advanced analysis techniques such as mixed models and/ or controls for students' initial persistence intentions. Our analyses improve on previous efforts to evaluate the STARS program by using an enhanced dataset and more sophisticated analysis techniques. A previous BPC grant provided funding to create a large, longitudinal dataset containing all of the survey data collected from STARS participants over the years, greatly expanding our sample size. This dataset has allowed us to employ advanced analysis techniques that allow for more nuanced and improved tests of our hypotheses.

5 RESEARCH QUESTIONS

Our analyses focus on answering the following research questions:

(1) Do students who spend more time per week participating in STARS activities have higher intentions to persist in computing?
(2) Do students who spend more semesters participating in the STARS program have higher intentions to persist in computing?
(3) Does STARS have enhanced impacts on the computing persistence intentions of students from historically marginalized gender and/or racial groups?
(4) Do some STARS activities have greater impacts than other STARS activities on students' intentions to persist in computing?

6 METHODS

6.1 Dataset

The data in this study was collected from the STARS program evaluation survey, which was administered from Fall 2006 - Spring 2017. Over this period, students from over 40 universities/colleges participated in the survey. This survey was administered via email twice per semester (at the beginning and end of the semester) to students who participated in STARS. The surveys were designed to measure the efficacy of STARS and contained a range of questions measuring students' feelings about computing, plans for their future, questions about their STARS experience, etc.

6.2 Participants

A total of 2,083 students completed at least one STARS survey during Fall 2006 - Spring 2017. Unfortunately, our sample is smaller than this, given that the respondent had to be an undergraduate student who provided answers to all of the survey questions used in our analyses. Given that survey questions varied throughout this timeframe, many students were not even presented with the option of answering all of these questions; thus, there is a great deal of missing data in our analyses (none of which we imputed). However, there do not appear to be gender or racial differences in missing data. Please see Tables 1 and 2 for the sample sizes of each presented model.

6.3 Measures

All measures were self-reported on the STARS surveys that were sent to participants each semester.

6.3.1 Computing Persistence Intentions (dependent variable). This construct is an index composed of four questions that were asked to participants in the post-semester surveys. This index was modeled after an existing index found to predict actual computing persistence [16]. Students were asked to indicate the extent to which they agreed/disagreed with four statements: 1) Participating in STARS increased my interest in graduate school, 2) Participating in STARS increased my interest in computing research, 3) Participating in STARS increased my commitment to my major, and 4) Participating in STARS increased my interest in my major. These Likert-type questions had options ranging from 1 (strongly disagree) to 6 (strongly agree). We averaged the responses from the STARS surveys to create the Computing Persistence Intentions index, which has a mean of 4.83. We calculated a Cronbach's alpha for this scale, to ensure that the scale created using our data was reliable [1]. The Cronbach's alpha reliability score for this scale was good (alpha=0.89).

6.3.2 Initial Persistence Intentions (independent variable). This index is comprised of four questions that were featured on the pre-semester survey that assessed students' initial intentions to persist in computing before joining the STARS program. Students were asked to indicate the extent to which they agreed/disagreed with four statements: 1) Focusing on computing/IT in graduate school is not a major priority for me (reverse coded), 2) I am interested in attending graduate school to do research, 3) I am interested in attending graduate school to learn more about computing/IT, and 4) I plan to stay in the field of computing long-term. These Likert-type questions included options ranging from 1 (strongly disagree) to 6 (strongly agree). We averaged the responses from the STARS surveys to create this index, which has a mean value of 4.59 with an acceptable alpha reliability score (alpha=.69).

6.3.3 Weekly time in STARS (independent variable). Students were asked to indicate the average number of hours they spent engaged in STARS activities each week. Since the option choices consisted of unbalanced ranges of hours (as opposed to a continuous time variable), we converted them to the midpoint of each choice to ease interpretation and to capture the underlying linear nature of the variable. Students could choose from 5 options: occasional (0-3 hours/month) (recoded as '0'), 1-2 hours/week (4-8 hours/month) (recoded as '1.5'), 3-4 hours/week (12-16 hours/month) (recoded as '3.5'), about 5 hours/week (18-22 hours/month) (recoded as '5'), or 6 or more hours/week (24+ hours/month) (recoded as '6'). This variable has a mean value of 3.43, meaning the average participant spent about three and a half hours on STARS activities per week.

6.3.4 Semesters in STARS (independent variable). Students were asked to indicate the number of semesters they had participated in STARS before completing a survey. This variable was a one-question measure and asked students: "How many semesters have you participated in the STARS Leadership Corps to date?" Students could respond with 0 or any positive value, or they could indicate that this was not applicable. Responses were recoded so that any students who participated in STARS for more than 10 semesters were recoded as 11 (there were only 9 participants who fell into this category, so this coding decision did not impact the results). This variable has a mean value of 2.19, meaning that most participants participated in STARS for two semesters/ one academic year.

6.3.5 Race (independent variable). Students were asked to indicate the race/ethnicity they most closely identify with. Students could respond by selecting one of the following: African American or Black, American Indian or Alaska Native, Asian or Pacific Islander, Caucasian or White, Hispanic Caucasian, Hispanic or Latino, Multirace or other (please specify), other (please specify), or Prefer not to specify. For the options of multiracial or other, as well as other, there was space for participants to write in their race/ethnicity. Race was *dummy coded* into multiple, individual variables for each race, meaning that a '1' was assigned for a given race if a respondent selected it, and '0' if they did not. 39.1% of the students in the sample identified as Black, 35.9% as white, 8.6% as Hispanic, 9.2% as Asian, and 7.2% as another race. In our models, White was used as the reference category and we included race as a predictor of computing persistence intentions, to explore whether participating in STARS had heightened impacts on students from historically excluded racial groups.

6.3.6 Gender (independent variable). Students were asked to indicate the gender they most closely identify with. Students could respond by selecting one of the following: Female, Male, or Prefer not to respond (dummy coded as '1' for a given gender if a respondent selected it, and '0' if they did not). 53.0% of the students in the sample identified as female, and 47.0% identified as male. In our models, Male was used as the reference category and we included gender as a predictor of computing persistence intentions, to explore whether participating in STARS had heightened impacts on women.

6.3.7 Class Standing. Students were asked to indicate their class standing at their college/university. Students could respond by selecting one of the following: freshman, sophomore, junior, or senior (dummy coded as '1' for a given class standing if a respondent selected it, and '0' if they did not). 6.1% of the students in the sample were freshmen, 15.9% were sophomores, 31.7% were juniors, and 46.2% were seniors.

6.3.8 Activity. Students were asked to indicate the "primary" activities they focused the majority of their time on while engaging in STARS. The options included engaging in K-12 Outreach (used as the reference category) (46.7% of the sample), becoming an intern at a local or national organization/business (4.8%), being mentored and/or mentoring other students (17.4%), being a peer ambassador at their university (17.0%), engaging in research with other students and faculty (8.7%), or some other activity (5.4%).

6.4 Analytical Approach

We use linear mixed-models to evaluate our research questions, as these models allow multiple independent variables to predict an outcome variable of interest (i.e., the dependent variable) [5, 18] while accounting for the non-independence of observations in the sample. While all of our models predict students' computing persistence intentions, our models vary in regard to: 1) which independent variables are used to predict computing persistence intentions (which are specified on the horizontal axes of Tables 1 and 2) and 2) the time at which persistence intentions were measured. These different operationalizations ensure the robustness of our results. To measure persistence, we use a student's first post-test survey in Models A and B, and a student's final post-test survey in Models C and D (Tables 1 and 2). In other words, we are using a single survey response from each participant in Models A-D. In Models E and F, we measure persistence using every survey response submitted by a given student, which creates a nested data structure (as observations are not independent, as individual survey responses are nested within participants) (Tables 1 and 2).

To account for the non-independence of observations, in Models A-D, observations (i.e., a single survey response) are nested within schools within semesters. In Models E and F, observations are nested within participants within schools within semesters. For an observation to be included in a model, it cannot have missing data for any variable included in the model. Thus, different models have different numbers of observations.

Table 1: Mixed Models Predicting Computing Persistence Intentions based on Hours per Week in STARS

	Persistence Measured after Students' First Semester		*Persistence Measured after Students' Final Semester*		*Repeated Measures of Persistence, Nested within Student*	
	Model A	Model B	Model C	Model D	Model E	Model F
Number of Participants	623	356	642	374	705	414
Observations (n=)	623	356	642	374	1197	746
Hours Per Week in STARS	0.03	0.07*	0.04	.07*	.06***	.10***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)
Woman	0.05	0.07	-0.03	0.00	-0.01	0.04
	(0.08)	(0.10)	(0.08)	(0.10)	(0.06)	(0.07)
Black	0.35***	0.50***	0.33**	0.54***	0.34***	0.47***
	(0.10)	(0.11)	(0.10)	(0.12)	(0.07)	(0.08)
Hispanic	0.38**	0.26*	0.45**	0.33	0.37***	0.30*
	(0.15)	(0.18)	(0.15)	(0.19)	(0.11)	(0.12)
Asian	0.21	0.28	0.32*	0.36*	0.22*	0.23†
	(0.14)	(0.16)	(0.15)	(0.18)	(0.10)	(0.12)
Other Race	0.30†	0.28	0.11	0.13	0.11	0.06
	(0.17)	(0.19)	(0.18)	(0.21)	(0.11)	(0.13)
Sophomore	-0.02	-0.03	-0.08	0.03	-0.05	-0.03
	(0.15)	(0.18)	(0.20)	(0.27)	(0.13)	(0.16)
Junior	-0.17	-0.11	-0.06	-0.05	-0.19	-0.15
	(0.15)	(0.18)	(0.19)	(0.26)	(0.13)	(0.15)
Senior	-0.16	-0.07	-0.08	-0.05	-0.14	-0.09
	(0.15)	(0.18)	(0.18)	(0.25)	(0.12)	(0.15)
Primary Intern	0.13	0.34	-0.15	0.16	-0.01	0.25
	(0.17)	(0.20)	(0.19)	(0.23)	(0.13)	(0.16)
Primary Mentor	-0.07	-0.00	-0.16	-0.07	-0.07	-0.04
	(0.12)	(0.14)	(0.12)	(0.14)	(0.08)	(0.09)
Primary Peer	0.03	-0.02	-0.12	-0.03	-0.02	0.01
	(0.12)	(0.14)	(0.12)	(0.14)	(0.08)	(0.09)
Primary Research	-0.04	-0.15	-0.11	-0.22	-0.05	-0.10
	(0.14)	(0.17)	(0.15)	(0.20)	(0.11)	(0.13)
Primary Other	0.01	-0.11	-0.36	-0.35	-0.13*	-0.12
	(0.17)	(0.20)	(0.18)	(0.21)	(0.13)	(0.14)
Initial Persistence Intentions		0.24***		0.21***		0.21***
		(0.05)		(0.05)		(0.03)
Intercept	4.68***	3.36***	4.69***	3.47***	4.68***	3.48***
	(0.17)	(0.30)	(0.21)	(0.35)	(0.14)	(0.23)

†$p \le .10$ * $p \le .05$ ** $p \le .01$ *** $p \le .001$

Note: In Models A-D, students are nested within schools, which are nested within semesters. In Models E and F, observations are nested within students, which are nested within schools, which are nested within semesters.

Table 2: Mixed Models Predicting Computing Persistence Intentions based on Duration/Semesters in STARS

	Persistence Measured after Students' First Semester		*Persistence Measured after Students' Final Semester*		*Repeated Measures of Persistence, Nested within Student*	
	Model A	Model B	Model C	Model D	Model E	Model F
Number of Participants	701	398	732	422	705	453
Observations (n=)	701	398	732	422	1316	810
Duration in the SLC Program	0.02	-0.00	0.03	0.06†	0.03†	0.05†
	(0.04)	(0.05)	(0.03)	(0.03)	(0.02)	**(0.02)**
Woman	-0.02	-0.01	-0.06	-0.04	-0.05	-0.01
	(0.08)	(0.09)	(0.08)	(0.10)	(0.06)	(0.07)
Black	0.40***	.53***	0.39***	0.56***	0.38***	0.47***
	(0.09)	(0.11)	(0.10)	(0.11)	(0.07)	(0.08)
Hispanic	0.35*	0.24	0.42**	0.35†	0.39***	0.33**
	(0.14)	(0.18)	(0.15)	(0.18)	(0.10)	(0.12)
Asian	0.30*	0.38*	0.43**	0.43*	.30**	0.28*
	(0.13)	(0.16)	(0.14)	(0.17)	(0.10)	(0.12)
Other Race	0.37*	0.24	0.24	0.23	0.20†	0.12
	(0.17)	(0.19)	(0.17)	(0.20)	(0.11)	(0.13)
Sophomore	0.05	0.05	-0.02	0.13	0.00	0.07
	(0.14)	(0.17)	(0.18)	(0.23)	(0.12)	(0.15)
Junior	-0.12	-0.03	-0.08	-0.02	-0.16	-0.06
	(0.14)	(0.17)	(0.17)	(0.22)	(0.12)	(0.14)
Senior	-0.11	0.03	-0.10	-0.03	-0.12	-0.01
	(0.14)	(0.17)	(0.17)	(0.21)	(0.12)	(0.14)
Primary Intern	0.15	0.20	-0.09	0.12	0.02	0.20
	(0.16)	(0.19)	(0.17)	(0.22)	(0.13)	(0.15)
Primary Mentor	-0.06	-0.05	-0.12	-0.12	-0.04	-0.06
	(0.12)	(0.14)	(0.12)	(0.14)	(0.08)	(0.09)
Primary Peer	0.02	-0.11	-0.05	-0.03	-0.01	-0.02
	(0.12)	(0.14)	(0.11)	(0.13)	(0.08)	(0.09)
Primary Research	-0.04	-0.11	-0.07	-0.06	-0.05	-0.04
	(0.14)	(0.16)	(0.14)	(0.18)	(0.10)	(0.12)
Primary Other	-0.00	-0.25	-0.28†	-0.43*	-0.12	-0.18
	(0.16)	(0.20)	(0.17)	(0.20)	(0.12)	(0.14)
Initial Persistence Intentions		0.21***		0.20***		0.20***
		(0.04)		(0.04)		(0.03)
Intercept	4.68***	3.63***	4.65***	3.56***	4.73***	3.67***
	(0.15)	(0.29)	(0.18)	(0.31)	(0.12)	(0.21)

†$p \le .10$ * $p \le .05$ ** $p \le .01$ *** $p \le .001$

Note: In Models A-D, students are nested within schools, which are nested within semesters. In Models E and F, observations are nested within students, which are nested within schools, which are nested within semesters.

7 RESULTS

7.1 R1: Do students who spend more time per week participating in STARS activities have higher intentions to persist in computing?

We find a statistically significant, positive relationship between hours per week in STARS and persistence intentions, no matter when we measure a student's intentions to persist in computing (i.e., first posttest, final posttest, mixed model with nested observations within students), once initial persistence intentions are held as a control (see Table 1, Models B, D, E, F). This means that students who dedicated more time to STARS activities each week indicated that they had a greater interest in staying within the computing field than students who spent fewer hours in STARS per week. Since this positive relationship is heightened when we control for students' initial intentions to persist, we know that highly committed students (who might be inclined to devote a lot of time to the STARS program *and* who might simultaneously have high intentions to persist in computing) are not driving this effect.

7.2 R2: Do students who spend more semesters participating in the STARS program have higher intentions to persist in computing?

We find a marginally significant relationship ($p < .10$) between semesters in STARS and persistence intentions, once we control for students' initial intentions to persist in computing and look at their latter survey response (Models D-F, Table 2). However, since this does not meet the $p < .05$ threshold for statistical significance, we do not feel confident enough in this relationship to report it as a finding. Future research should explore this relationship in more detail.

7.3 R3: Does STARS have enhanced impacts on the computing persistence intentions of students from historically excluded gender, racial, and/ or ethnic groups?

We find evidence that STARS participation has enhanced impacts on students who identify as African-American/Black (in comparison to White students) no matter when we measure a student's intentions to persist in computing, or what controls we include in the model (see Table 1, Models A-F, and Table 2, Models A-F). We generally find that STARS participation has enhanced effects on Hispanic students (in comparison to White students) (see Table 1, Models A, B, C, E, and F, and Table 2, Models A, C, E, and F), but there are some model specifications in which the relationship is not statistically significant (see Table 1, Model D, and Table 2, Models B and D). However, we find no evidence that STARS has enhanced impacts on women in comparison to men, as gender was never statistically significant (see Table 1, Models A-F, and Table 2, Models A-F).

7.4 R4: Do some STARS activities have greater impacts than other STARS activities on students' intentions to persist in computing?

We do not find a statistically significant relationship between STARS activities and persistence intentions in the majority of models (see Tables 1 and 2). While there are three models in which "Primary other" was significant or marginally significant (Table 1, Model E and Table 2, Models C and D), we do not feel confident enough in this relationship to report it as a finding. Future research should explore this in more detail. In general, the fact that primary activities do not seem to have differential impacts on persistence may mean that as long as students are engaged in STARS, the effects are similar no matter what activity they participate in.

8 DISCUSSION

We evaluated whether the STARS Computing Corps program, a multi-pronged BPC initiative funded by the NSF designed to increase participation in computing (especially among students from historically marginalized groups) meets its stated goals by examining how participating in STARS is related to students' intentions to persist in computing. Across models, we found that students who spent more time participating in STARS' activities each week had higher intentions to persist in computing, even after controlling for their initial intentions to persist in computing. Furthermore, we found that participating in STARS had a larger positive impact on the persistence intentions of Black and Hispanic students than White students. In sum, we consider this to be robust evidence for the efficacy of STARS, given that we found the same pattern of results in the majority of models. More broadly, these findings provide evidence for the efficacy of the STARS program and other multi-pronged interventions aimed at increasing the persistence intentions of students in computing.

However, we did not find evidence for a number of our hypotheses: specifically, we did not find evidence that the number of semesters a student spent in STARS was predictive of their intentions to persist in computing, that STARS had an enhanced impact on women, or that the activity a student participated in during STARS impacted their persistence intentions.

8.1 Recommendations

These results suggest that multi-pronged programs designed to increase participation in computing would be wise to focus on the intensity of participation (i.e., the number of hours per week a student spends participating) as opposed to the length of time participating (i.e., the number of semesters a student is involved in the program). Given that we found that STARS had increased positive impacts on Black and Hispanic students, these results also provide evidence that a student's identity moderates the efficacy of interventions designed to impact their persistence in computing. While this conclusion has been reached by other researchers, [12] it is noteworthy that we found this effect even within a BPC program that focused on increasing computing persistence for members of all historically excluded groups, yet there were still enhanced impacts for members of some groups in comparison to others.

8.2 Limitations

This study has a few important limitations to address. First, the participants represented in this data set were not tracked after their time in STARS. Thus, this paper cannot be used to definitely conclude that participation in STARS leads to the completion of a computing degree or retention in the field of computing. [23]. Future studies on the STARS Computing Corps could benefit from obtaining career and degree information from past participants to make claims about the program's long-term impact on persistence in computing. Second, despite the robustness of our results and our controls, we are unable to make a causal claim between hours of STARS participation and computing persistence as there was no random assignment to condition. Third, our models only accounted for about 13-15% of the variance in persistence intentions in the field of computing, meaning that many other variables contribute to persistence intentions that were not measured or not included in our models (for instance, students' experiences in their computing classrooms). Future research should include more measures to better predict persistence. Finally, because this data was drawn from self-reported surveys, many individuals participated in STARS but took only the pre-survey, only the post-survey, or neither of the surveys. This means that while all students are presented with the opportunity to take these surveys, not all choose to do so. Thus, we are missing data on the experiences of many students, and there may be systematic differences in those who decided to respond.

9 CONCLUSION

The STARS program, and other multi-pronged programs like it, work to make computing in higher education more accessible to all students, especially those who do not fit into the dominant computing culture. This is accomplished by STARS providing historically excluded students with access to unique and tailored activities aimed at promoting their success and persistence in the field of computing. The results from this study suggest that STARS meets its goals, as the amount of hours STARS students engage with this program is positively associated with their intentions to persist in computing (especially among Black and Hispanic students), even controlling for their initial intentions to persist in computing. Additionally, multi-pronged programs like STARS should focus on the intensity of participation (as opposed to the length of participation or a particular activity) to increase students' desire to persist in computing careers.

10 ACKNOWLEDGMENTS

This material is based upon work supported by the National Science Foundation under Grant No. 2022660, 2023391, 2023399, 2023400, and 2137369.

REFERENCES

[1] Katie Anne Adamson and Susan Prion. 2013. Reliability: measuring internal consistency using Cronbach's α. *Clinical simulation in Nursing* 9, 5 (2013), e179–e180.

[2] William Aspray. 2016. The broadening participation in computing alliances. *Participation in computing: The National Science Foundation's expansionary programs* (2016), 53–102.

[3] Tiffany Barnes, Teresa Dahlberg, Kim Buch, and Karen Bean. 2009. The STARS leadership corps: An innovative computer science learning community. *Learning Communities Journal* 1, 2 (2009), 5–18.

[4] Karen Bean, Teresa Dahlberg, Tiffany Barnes, Audrey Rorrer, and Linda Cagley. 2014. An innovative partnership between national and regional partnerships: STARS meets McPIE. *PRISM: A Journal of Regional Engagement* 3, 2 (2014), 119–130.

[5] Benjamin M Bolker. 2015. Linear and generalized linear mixed models. *Ecological statistics: contemporary theory and application* (2015), 309–333.

[6] Kristy Elizabeth Boyer, E Nathan Thomas, Audrey S Rorrer, Deonte Cooper, and Mladen A Vouk. 2010. Increasing technical excellence, leadership and commitment of computing students through identity-based mentoring. In *Proceedings of the 41st ACM technical symposium on computer science education.* 167–171.

[7] STARS Computing Corps. 2023. *STARS Computing Corps: About Us.* https://www.starscomputingcorps.org/about-us/

[8] STARS Computing Corps. 2023. *STARS Computing Corps: Partners.* https://www.starscomputingcorps.org/partners/

[9] Haley Crews, Tiffany Barnes, Joshua Pollock, Susan R Fisk, Jamie Payton, Tom McKlin, Audrey Rorrer, Rachel Harred, and Veronica Catete. 2022. Investigating Impacts of STARS Program Components on Persistence in Computing for Black and White College Students." Accepted at Research in Equity and Sustained Participation in Engineering, Computing, and Technology (RESPECT). *Research in Equity and Sustained Participation in Engineering, Computing, and Technology (RESPECT)* (2022).

[10] Teresa Dahlberg, Tiffany Barnes, Kim Buch, and Karen Bean. 2010. Applying service learning to computer science: attracting and engaging under-represented students. *Computer Science Education* 20, 3 (2010), 169–180.

[11] Teresa Dahlberg, Tiffany Barnes, Kim Buch, and Audrey Rorrer. 2011. The STARS alliance: Viable strategies for broadening participation in computing. *ACM Transactions on Computing Education (TOCE)* 11, 3 (2011), 1–25.

[12] Susan R. Fisk, Brittany Watts, Courtney Dress, Charlotte Lee, Audrey Rorrer, Tom McKlin, Tiffany Barnes, and Jamie Payton. 2023. Retaining Black women in computing: A comparative analysis of interventions for computing persistence. *Accepted with revisions at ACM Transactions on Computing Education* (2023).

[13] Patricia Garcia, Melissa Perez, Devon Farrell, Sarah Bork, Barbara Ericson, and Joi-Lynn Mondisa. 2021. Supporting Mutually Beneficial Near-Peer Mentoring Relationships Within Computing Education Programs. In *2021 Conference on Research in Equitable and Sustained Participation in Engineering, Computing, and Technology (RESPECT).* IEEE, 1–9.

[14] Michail N Giannakos, Ilias O Pappas, Letizia Jaccheri, and Demetrios G Sampson. 2017. Understanding student retention in computer science education: The role of environment, gains, barriers and usefulness. *Education and Information Technologies* 22 (2017), 2365–2382.

[15] Mark J Graham, Jennifer Frederick, Angela Byars-Winston, Anne-Barrie Hunter, and Jo Handelsman. 2013. Increasing persistence of college students in STEM. *Science* 341, 6153 (2013), 1455–1456.

[16] Rachel Harred, Tiffany Barnes, Susan R Fisk, Bita Akram, Thomas W Price, and Spencer Yoder. 2023. Do Intentions to Persist Predict Short-Term Computing Course Enrollments: A Scale Development, Validation, and Reliability Analysis. In *Proceedings of the 54th ACM Technical Symposium on Computer Science Education V. 1.* 1062–1068.

[17] Penelope M Huang and Suzanne Gage Brainard. 2001. Identifying determinants of academic selfconfidence among science, math, engineering, and technology students. *Journal of women and minorities in science and engineering* 7, 4 (2001).

[18] Gareth James, Daniela Witten, Trevor Hastie, Robert Tibshirani, and Jonathan Taylor. 2023. Linear regression. In *An Introduction to Statistical Learning: with Applications in Python.* Springer, 69–134.

[19] Wayne W LaMorte. 2022. The theory of planned behavior. *Boston University School of Public Health* (2022).

[20] Lina Lee, Celine Latulipe, and Tonya Frevert. 2022. Using Discrimination Response Ideation to Uncover Student Attitudes about Diversity and Inclusion in Computer Science. *ACM Transactions on Computing Education* 22, 4 (2022), 1–32.

[21] Michael J Lee. 2019. Increasing minority youths' participation in computing through near-peer mentorship. *Journal of computing sciences in colleges* 35, 3 (2019).

[22] CJ Libassi. 2018. The neglected college race gap: Racial disparities among college completers. (2018).

[23] David M Merolla, Richard T Serpe, Sheldon Stryker, and P Wesley Schultz. 2012. Structural precursors to identity processes: The role of proximate social structures. *Social psychology quarterly* 75, 2 (2012), 149–172.

[24] Rachel L Navarro, Lisa Y Flores, John-Paul Legerski, Julio Brionez, Sarah F May, Han Na Suh, Diana R Slivensky, Feather Tapio, Hang-Shim Lee, Patton O Garriott, et al. 2019. Social cognitive predictors of engineering students' academic persistence intentions, satisfaction, and engagement. *Journal of Counseling Psychology* 66, 2 (2019), 170.

[25] Maria Ong, Janet M Smith, and Lily T Ko. 2018. Counterspaces for women of color in STEM higher education: Marginal and central spaces for persistence and success. *Journal of research in science teaching* 55, 2 (2018), 206–245.

[26] Crystal L Park, Michelle K Williams, Paul R Hernandez, V Bede Agocha, Lauren M Carney, Andrea E DePetris, and Sharon Y Lee. 2019. Self-regulation and STEM persistence in minority and non-minority students across the first year of college. *Social Psychology of Education* 22 (2019), 91–112.

[27] Jamie Payton, Tiffany Barnes, Kim Buch, Audrey Rorrer, and Huifang Zuo. 2015. The effects of integrating service learning into computer science: An inter-institutional longitudinal study. *Computer Science Education* 25, 3 (2015), 311–324.

[28] Jamie Payton, Tiffany Barnes, Kim Buch, Audrey Rorrer, Huifang Zuo, Kinnis Gosha, Kristine Nagel, Nannette Napier, Ebrahim Randeree, and Lawrence Dennis. 2016. Stars computing corps: Enhancing engagement of underrepresented students and building community in computing. *Computing in Science & Engineering* 18, 3 (2016), 44–57.

[29] Jamie Payton, Tiffany Barnes, Audrey Rorrer, Kimberly Buch, and Kristine Nagel. 2016. Launching STARS computing corps: Engaging faculty and student leaders to broaden participation. *ACM Inroads* 7, 4 (2016), 61–64.

[30] Rachael D Robnett. 2016. Gender bias in STEM fields: Variation in prevalence and links to STEM self-concept. *Psychology of women quarterly* 40, 1 (2016), 65–79.

[31] Audrey S Rorrer, Tiffany Barnes, Jamie Payton, and Huifang Zuo. 2019. Challenges and opportunities in evaluating broadening participation in computing: The STARS evaluation cohort model. *2019 Research on Equity and Sustained Participation in Engineering, Computing, and Technology (RESPECT)* (2019), 1–5.

[32] Kelsey C Thiem and Nilanjana Dasgupta. 2022. From precollege to career: Barriers facing historically marginalized students and evidence-based solutions. *Social Issues and Policy Review* 16, 1 (2022), 212–251.

[33] Carla B Zoltowski and William C Oakes. 2014. Learning by doing: Reflections of the EPICS program. *International Journal for Service Learning in Engineering, Humanitarian Engineering and Social Entrepreneurship* (2014), 1–32.