Scientific Skills, Identity, and Career Aspiration Development from Early Research Experiences in Computer Science

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ABSTRACT

The computer science research workforce is characterized by a lack of demographic diversity. To address this, we designed and evaluated an end-to-end mentored undergraduate research intervention to nurture diverse cohorts' skills for research and develop their vision of themselves as scientists. We hypothesized that this intervention would (a) grow scientific skills, (b) increase science identity, and (c) stimulate students to view scientific careers in computer science as future viable options. The evaluation of the hypotheses addressed the limitations in self-evaluation with a multicomponent evaluation framework, comprising five forms of evidence from faculty and students, engaging on team projects, with cohorts additionally participating in professional development programming. Results indicated that students gained in scientific skills and broadened their identity as scientists and, to some degree, strengthened their outlook on research careers. The introduced structured intervention and evaluation framework were part of a US National Science Foundation Research Experiences for Undergraduates (REU) computing-focused summer program at Rochester Institute of Technology and are applicable in other scientific disciplines and institutional settings.

KEYWORDS

Undergraduate computing research; Scientific skills, identity, and career aspirations; Diversity in research

1 INTRODUCTION

Despite being well-documented and extensively debated, underrepresentation among women, AALANA (African American, Latino/a American, Native American), and persons with disabilities in computer science continues to persist, according to US national statistics compiled by the National Science Foundation and the National Center for Science and Engineering Statistics [39]. The level of underrepresentation among these groups is striking in PhD education where the focus is on training graduates to pursue careers as scientists in academia, industry, and government. Table 1 highlights the disparity between the pre-pandemic 2018 US general population estimates, obtained from the the United States Census Bureau [51], and the percentage of doctoral degrees awarded at US public and private Computer Science departments reported by the Computing Research Association [14]. While we report on proportions from 2018 to emphasize that the information was not related to the pandemic, data from 2020 show similar trends. Moreover, while proportions may differ somewhat across data sources, evidence clearly points to a lack of diversity among computer science researchers. Furthermore, data analyzed by the Equity in Graduate Education Resource Center indicates that the proportion of women PhD graduates is lower in computer science compared to other science and engineering disciplines, with even more inequities when considering race and gender together [18].

Responding to the need for increasing diversity and inclusion in the computer science research workforce, we study the impact—for diverse student cohorts—of participating in an end-to-end undergraduate research training program. The theme of the program focused intellectually on sensing humans computationally, using hardware and software. We hypothesize that early research experiences in computing for diverse cohorts will:

(a) grow scientific skills,
(b) increase science identity, and
(c) stimulate students to view scientific careers in computer science as future viable options.

By *scientific skills*, we focus on research skills and knowledge for computer science, thus involving broader scientific skills such as teamwork and science dissemination, and also disciplinary-specific abilities such as computer programming and human subjects research competence in addition to core research process skills such as formulating research questions, finding relevant research literature, and articulating the limitations of different methodological approaches. As discussed by Kim and Sinatra [29], *science identity* is a complex socio-cultural construct, intertwined with self/other recognition as being a researcher and important for retaining people in research, following Carlone and Johnson [9]. We focus here on the perception of belonging, and development into belonging, to the community of practice of computer science research. We also attend to the goal and visions for future *scientific careers in computer science* by examining aspirations for graduate school and progression toward careers as scientists. As detailed below, to examine the above hypotheses, we utilize multi-component evaluation, using data from three years of demographically diverse undergraduate student cohorts and mentors who participated in the early mentored research intervention.

1.1 Early Mentored Scientific Experiences in STEM

It is widely acknowledged that undergraduate research experiences bring positive benefits. Hammack et al., who link mentoring to

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Table 1: Comparing population estimates from the 2018 US Census Bureau against the 2018 Taulbee Survey's information on awarded Computer Science doctoral degrees points to a striking underrepresentation of women and AALANA among computer scientists with terminal research degrees. This reaffirms the need for opening up research careers among underrepresented groups early with effective undergraduate research training programs that are evaluated holistically by considering multiple evidence and not just self-assessment.

Demographic	Population estimate	CS PhDs awarded
American Indian or Alaska Native	1.3%	0.1%
Black or African-American	13.4%	1.4%
Hispanic	18.3%	1.8%
Women	50.8%	19.3%
Persons with a disability	8.7%	Not reported

"coaching and apprenticeship" (p. 10), note that mentoring provides multiple positive outcomes for the undergraduate student receiving the mentee experience and cognitive development directly through research [25]. Additionally, analysis from biological/life sciences undergraduate research reveal that mentoring guidance influences students' perceptions of their own research competencies, as observed by Byars-Winston et al. [7]. Wright reported on responses to a survey of almost 800 students by the Computing Research Association's Center for Evaluating the Research Pipeline [56]. The results indicated that the proportion of computing students who applied to graduate school approximately doubled if undergraduates experienced research formally and also roughly doubled decisions to enroll in PhD studies. The National Academies of Sciences, Engineering, and Medicine summarized several considerations and findings about mentoring in undergraduate research in STEM fields such as the many types of mentors there can be, the many guises that mentors can adopt and skill development they can support, the results there can be for faculty and students, existing mentoring-related measurements, as well as the data linking mentoring and academic achievements [37]. Johann and Turbak highlighted the growth provided through a research experience [28] as it "enables undergraduates to make the transition from course-directed consumption of scientific knowledge to participation in the production of knowledge" (p. 280). They reported on a computer science undergraduate research program involving principles of "open-ended closed-endedness" (p. 285)–providing clear objectives for research while ensuring intellectual room for new discoveries–and "structured flexibility" (p. 286)–offering students clear guidance and intellectual freedom concurrently. Similarly, Skorinko emphasized the importance of research for stimulating students, and to engage diverse students, through scholarly experiences at an early stage of their undergraduate careers [46]. Cohoon et al. noted that more undergraduates benefiting from mentoring in research indicated higher likelihood to attend graduate school at highly regarded institutions [12]. In addition, Baker et al. summarized reported benefits to mentors of undergraduate researchers, and observed a positive link between faculty who mentored undergraduate researchers and faculty professional productivity such as being active in publishing research, in pursuing funded research, and in engaging in conferences [3]. Hall et al. observed the importance of mentors' and their institutional environments' recognition of such benefits [24]. In addition, Alvarado et al. reported on findings from analyzing sophomore (second-year) university students who majored in computer science or a related field while participating in a program structured around groups; when comparing to groups of control peers, outcomes pointed to benefits for participant students in terms of grade point average; and there were potential benefits in terms of being confident and growth of research interest [2]. The study presented here recognizes the centrality of mentoring and mentee-mentor interaction in early research experiences, operationalized by integrating both the perspective of students and faculty mentors for examining our hypotheses.

1.2 Diverse Students' Science Identity and Early Scientific Experiences

Prior STEM education literature recognizes mentored research experiences as a mechanism toward broadening participation. Barker noted that students who engage in research as undergraduates are more likely to pursue graduate degrees [5], and Estrada et al. emphasized that it aided students to stay in STEM [19]. Tamer and Stout conducted an analysis with women and men from underrepresented groups and arrived at four factors impacting study participants' intention to pursue academic professorial careers [48]. These included research project collaboration, learning about the graduate student experience and how to apply to graduate school, and gaining insight into how computer science research careers can impact society. Additionally, Tamer and Stout [48] observed that "[b]y promoting interest in the professorate among URMW [defined as "underrepresented men as well as women"] undergraduate students, REUs [research experiences for undergraduates] have the capacity to diversify the types of role models that future generations of women, and men from racial minority groups interact with and aspire to become" (p. 118).

Still, there is much room for improvement and growth of such formative training opportunities, and especially for new empirical study of outcomes from computer science undergraduate research training. Indeed, just two decades ago Johann and Turbak pointed out that computer science lacks the strong tradition of undergraduate research which exists in other science disciplines or in engineering fields [28]. Kim et al. observed that while most of their surveyed undergraduate research programs specifically targeted women, and also mostly successfully recruited a majority of women participants, the men in these programs still felt more confident in their abilities and accomplishments for moving forward in STEM disciplines post-program despite similar performance of the women students [30].

Results produced by Estrada at al. suggested that identifying as a scientist was highly important for downstream making STEM one's career, as opposed to other professions [19]. They noted that "higher education institutions that provide authentic experiences of belonging and inclusion, which are components of science identity, may be more likely to increase their URM [defined as "historically underrepresented minorities"] retention rates" (p. 11).

Follmer et al. noted that, compared to undergraduate research experiences organized by institutions, nationally-spanning programs were more diverse and also able to accommodate individuals without opportunities to engage in research experiences at their respective institutions [20]. The US National Science Foundation offers a program that enables Research Experiences for Undergraduates Sites (cohort-based seasonal programs), recognizing these programs as "an important means for extending high-quality research environments and mentoring to diverse groups of students" and it also aims to reach students "from academic institutions where research programs in STEM are limited" [38]. In general, for inclusive mentoring a diverse mentoring team is important. This includes the involvement of female role models as noted by Doerschuk [16]. Shamir noted the importance of "a broad range of interdisciplinary research topics that can engage and motivate students" (p. 15) [44]. Interdisciplinary projects can help peak computer science undergraduate students' interests. In particular, the program discussed focused on computational sensing research projects linked to motivating applications in impactful societal domains such as education, wellness, smart living, and leisure.

1.3 Science Skills and Identity Development in Mentored Experiences

The notion of "*cognitive apprenticeships*" discussed by Griese et al. [22] and earlier by Collins et al. [13] provided a theoretical lens in this study for examining growth of science skills and science identity in mentored research experiences in computing, and aspirations for pursuing scientific careers. Marra and Pangborn emphasized the value of apprenticeship for engineering skills [34], and Charney et al. reported on how elements of cognitive apprenticeship were adapted in high school-level research-infused experiences involving science, resulting in knowledge gains [10]. The present study connected mentoring to apprenticeship/coaching experiences in computer science research. Childress et al. highlighted the distinction between supervising and mentoring–while providing supervision and support for daily scientific activities is important, mentoring extends beyond supervision into supporting students to enter into and become familiar with the research community and envision themselves as a researcher, which may nurture interests to choose a research career path [11]. Additionally, the Social Cognitive Career Theory (SCCT), introduced by Lent et al. [32], relates to Bandura's *self-efficacy* concept [4] (in the context of the present study: confidence in one's competency to pursue a research career path). It can provide a basis for examining student attitudes about educational career choices as computer scientists as exemplified by Alshahrani et al.'s work [1]. Thiry et al., discussing socio-cultural theoretical perspectives, further remarked that development is influenced by participating in a community where activities are experienced and reflected upon directly [49]. Highlighting the benefits of team science, Johann and Turbak argued that structuring computer science undergraduate research as a collaboration endeavor nurtured students persevering in research activities beyond a time-limited program [28]. Holcomb et al. also observed a need for exposing students to collaboration in a brief programming-focused summer school [26]. Similarly, Sturner et al. noted the value of nurturing teamwork competency in research [47]. These theoretical foci and observations framed the present study.

1.4 Evaluating Science Skills and Science Identity

Shanahan et al. [45] observed that much prior work had been based on self-reporting, covering either perceptions of students, whose ratings of own skills may not correspond well to actual research training achievements, which have been shown to be better determined by faculty, as discussed by Griese et al. [22], or faculty perceptions of undergraduate mentoring. For example, Baker et al. explored faculty perceptions of enabling or limiting factors for undergraduate research mentoring based on focus group data [3]. Thiry et al. [49] noted that self-reporting might be particularly beneficial for understanding advancement in "confidence or interest in a subject" (p. 382), yet it is not the only way to measure educational gains. Instead, as discussed by Linn et al., evaluation of experiential research training will benefit from a comprehensive, holistic approach that relies on multiple, complimentary forms of evidence [33]. In addition, Griese et al. emphasized the importance of considering both roles—mentor and protégé—when studying mentoring in academic contexts [22].

The design and use of a holistic evaluation framework is one of the differentiators that sets the present work apart from prior studies on programs for undergraduate research training, in combination with its assessment of development of scientific skills, identity, and the exploration of seeing oneself as becoming part of a community of research practice in computer science. In contrast, for example Miller et al. focused on student self-report data [36]. We also go beyond the evaluation by Jelen et al. which included student self-report measurements (surveys, interviews), briefly summarized answers to a mentor survey that highlighted time commitments (time spent on mentoring undergraduates, coaching graduate mentors, and perception on usefulness of time investment), and individual "stakeholder insights" (p. 993) narratives [27]. Moreover, this work differs through its examination of an end-to-end early research experience intervention with integrated professional development activities. Considering five forms of evidence, this study assessed the development of research identities, skills, and aspirations for future participation in the computer science research community.

2 MATERIALS AND METHODS

Our mentored undergraduate research intervention and evaluation framework were deployed as part of a US National Science Foundation Research Experiences for Undergraduates summer research program at Rochester Institute of Technology. The intellectual research theme was focused on computational sensing of humans and the program recruited ten undergraduate students annually from across the United States for a 10-week summer research experience. In addition to engaging in team-based research projects, participating students were also exposed to a suite of programmatic activities designed to grow scientific and career skills and stimulate their view of scientific careers as viable options.

2.1 Participants

Across three cohort years, there were 30 students in total from diverse demographic backgrounds, outlined in Figure 1. In addition, students came from 26 distinct institutions, with most characterized by limited opportunities for computer science research. While attempts were made to engage students from across the USA, more came from the US Northeast given its concentration of universities and colleges. The students participated in 15 team-based computer science research projects, with gender-balanced pairs of students being mentored per project. Of 15 faculty mentors who guided the research experiences, 40% participated all three years and one third in one year. A third of faculty were women. The mentors represented varying ethnic and national backgrounds.

2.2 Early Research Experience Intervention

For ten summer weeks, students experienced engaging in scientific practices. The research projects centered on sensing and analyzing human behaviors and cognitive processes using computer science. Additionally, a preparatory pre phase (e.g., completion of human subjects research certification and an introductory programming course) and a dissemination-focused post phase (with remote meetings with mentors) extended the 10-week experience. The approximate annual timetable of the early research experience in which students participated is in Figure 2. Prior work on undergraduate research training has also highlighted the importance of thoughtful, year-long logistical pre-program planning [55]. Our intellectual theme focused on basic research in the *acquisition*, *fusion*, and *analysis* of multimodal human sensing data. The ten weeks had a two-fold structure: (1) students conducted a team science research project with mentors and (2) they also participated in professional development activities as a cohort (see overview in the Appendix and Figure 3) centered on research and graduate school competencies and knowledge.

Research projects were structured as scaffolded team-science experiences spanning experimental design, data acquisition, analysis and inference with collected data including data visualization, and dissemination with deliverable milestones. Projects provided experience with human subjects experiments including collection and analysis of multimodal human-elicited data, and students participated in the Institutional Review Board (IRB) ethics review application process. The team science structure adopted in the training program involved regular student-student and student-faculty interactions.

Johann and Turbak highlighted the challenge of conducting a research project in a short time span such as just ten weeks [28]. To mitigate this issue, the *pre-program phase* engaged students with preparatory research activities — online human-subjects training and an online computer programming course. Faculty mentor teams also assigned project-relevant pre-readings to bring students up to speed on key relevant research before the program started. The pre-program activities required a reasonable time commitment, recognizing that students were also concluding their regular semester activities. The time-progression of the ten-week *in-program*

	2016-2018 average 3-yr target	2016	2017	2018	Average 3-yr actual
Cohort (+ other participants)	10	**10** (+ 1)	**10** (+ 1)	**10** (+ 2)	**10**
%Women (*43%)	20%	**50%**	**50%**	**50%**	**50%**
% URM (*37%)	20%	**30%**	**30%**	**30%**	**30%**
% Outside home institution	75%	**80%**	**90%**	**100%**	**90%**
% Computing majors	60%	**70%**	**80%**	**90%**	**80%**
% Limited CS research opportunities	60%	**60%**	**60%**	**60%**	**60%**
% Earlier than college junior	25%	**50%**	**30%**	**40%**	**40%**
% With disability	20%	**30%**	10%	**20%**	**20%**
% Other	20%	**30%**	10%	10%	17%

Figure 1: Student demographics. *Other participants* refer to additional undergraduates who participated in mentoring, research, and program activities but not in the evaluation. Comparison averages (*) are aggregates for nationwide undergraduate research training programs from Raicu et al. [41]. Green and bold: Met/exceeded the average 3-year targets set by the program organizers.

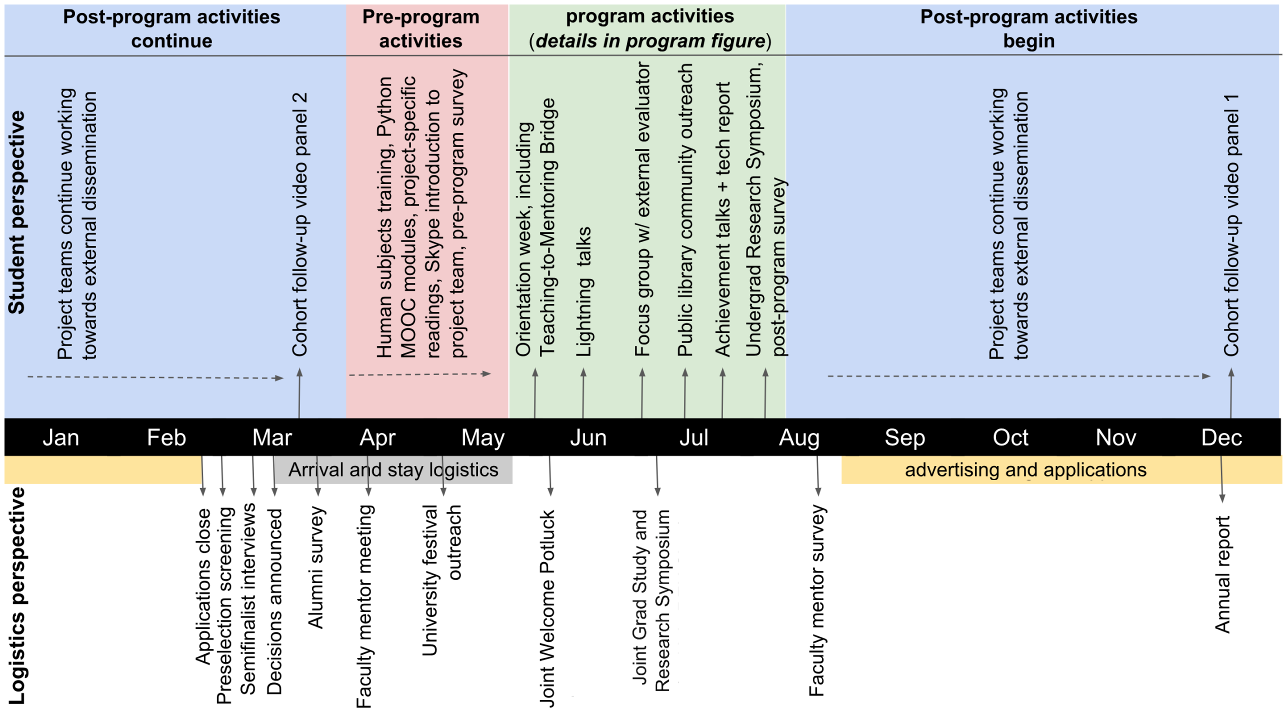


Figure 2: Timetable of annual program logistics. The upper half conveys the student perspective and the lower half organizational logistics. Program details (green interval) are expanded in Figure 4 for the 10-week program.

Figure 3: Professional development activities. A: Workshops with active learning-by-doing. B: Panel discussing grant writing for graduate school with students. C: Public STEM outreach event. D: Coordinated interdisciplinary symposium about graduate school and research. E: Post-program video follow-up. Faces have been blurred for anonymity.

experience is depicted in Figure 4. The leftmost column outlines progression in the research process. A *post-program phase* continued team interaction for external dissemination as well as cohort follow-up with video gatherings and support in the graduate school application process. Students were also encouraged to seek out new research experiences either at their home institutions after the program ended or at other universities. This was motivated by a finding by Estrada et al. [19] using a statistical model that two semesters in undergraduate research “uniquely predict overall science self-efficacy, identity, and values” (p. 10).

Based on a review of numerous publications, Walkington et al. converged on ten beneficial strategies when mentoring undergraduate researchers [52]. Almost all were operationalized structurally in the intervention. For example, we planned ahead for the research process in the pre-program phase; made expectations clear for anticipated outcomes during orientation; provided a challenging as well as emotionally supporting environment; promoted team-building with field trips and joint meals; encouraged gradually increased research independence; enabled networking opportunities in coordinated events and formally discussed disciplinary practices in a journal club and non-credit course; and provided support in scholarly dissemination post-program.

2.3 Multicomponent Evaluation

Inspired by the STEM and computer science mentoring and early research training literature, the evaluation framework integrated both subjective self-reported and objective program-level measures. We considered five forms of evidence (E1–E5) described below. Participating students and mentors consented to completing assessments, and this work was IRB-approved. We focus on measures of proportions and central tendency as well as qualitative responses; Linn et al. noted that experiential reflection was beneficial in undergraduate research experiences [33].

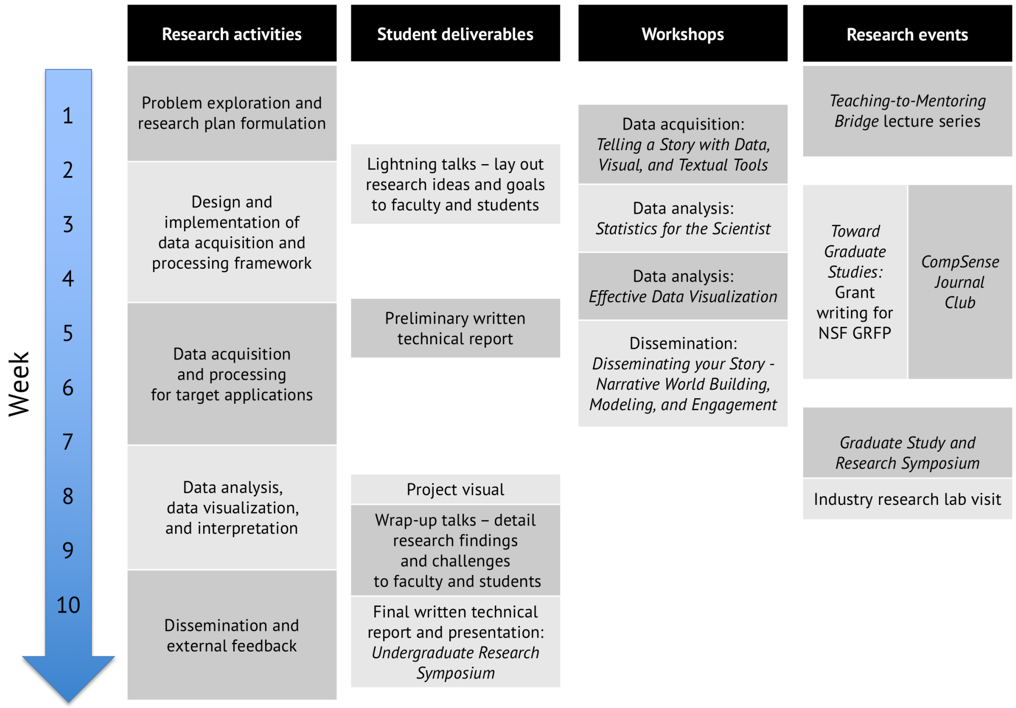


Figure 4: Timeline of the 10-week program, with sequenced steps of the research process. After the initial year, professional development activities were front-loaded to prioritize focus on research later in the program.

2.4 E1: Faculty-assessed Student Skills (Repeated In-program Measures)

Students were individually assessed in three formal *mentor reports* with 33 assessed skills using five-point Likert scale ratings (*strongly disagree* to *strongly agree*) spread out across the summer, administered approximately every three weeks. Skills assessed, in part adapted from a program at Willamette University [54], are listed in Table 2. For example, mentors assessed the student's ability to find, filter, and apply technical scientific information to their project, initiative-taking and time management skills, capability of formulating research questions, ability to deploy sound methodological practices, problem solving and creative skills, ability to link theory with empirical work, presentation and technical writing skills, etc. Additional assessed skills focused on the discipline such as computer software and hardware, software development and computer programming, etc. There were not multiple raters, and for this reason inter-rater reliability measurements are not reported. The analysis focused on whether individual skills, and how many skills in total, were assessed as increasing over the course of the program. (We do not compare the means since in this case, the Likert scales elicit subjective ratings and raters may adopt different calibration strategies.)

2.5 E2: Student Self-assessed Skills and Benefits (Pre and Post Measures)

A program-independent evaluator elicited student self-assessment data in pre and post surveys. As shown in Figure 2, the pre survey occurred right before the start of the program and the post survey in the 10th week of the program. Students assessed their level pre and post (*How would you rank your skill level in the following areas?*) for theoretical or applied scientific skills (research ethics, understanding and critiquing research literature, formulating research questions) and disciplinary-specific skills (programming and system development, human subjects research) on an ordinal 5-point scale. The analysis computed gains in the proportion of students that assessed themselves as being high-skilled, i.e., as *Master, Expert* or *Proficient* vs. low-skilled, i.e., *Familiar* or *Beginner*, given the difference between pre to post self-assessment. In addition, in the post survey, students self-assessed benefits of the early scientific research experience to their development of skills (*Please indicate to what extent the program benefited you for each*) on a 4-point ordinal scale (from *not at all* to *a great extent*). We computed the proportion of students reporting benefits (*somewhat* or *a great extent* ratings), leaving out those who did not (*not at all* or *very little* ratings). These benefits assessed involved scientific skills (such as learning ethical conduct in research, ability to analyze data and interpret results, tolerance for obstacles faced in research), scientific identity (increased academic self-confidence, understanding how researchers think and work on problems), and research career aspirations (readiness for more demanding research, increased confidence in potential for academic career). Lastly, two summative metrics focused on career plans—intent to pursue graduate school in a STEM field or a non-STEM field.

Table 2: Skills mentors assessed three times at approximately three-week intervals (n = 10; 30 annually). Items began with *The student...* except for S20, S22, S23, and S26. The right-most columns indicate items for which average ratings increased across all three assessment opportunities; this applied more to Y2 and Y3. Missing ratings could occur for lack of assessment evidence; these were excluded.

ID	Skill assessed	Y1	Y2	Y3
S1	is a capable programmer/software developer.		✓	✓
S2	is capable of finding relevant research resources (software, datasets, literature, etc.)		✓	✓
S3	is capable of adapting to unfamiliar software.		✓	✓
S4	is capable of adapting to unfamiliar equipment/hardware.		✓	✓
S5	takes initiative in research tasks beyond what is assigned.			✓
S6	demonstrates eagerness to learn about forms of data she/he has not worked with before.		✓	
S7	understands technical/scientific literature.	✓	✓	
S8	applies insights from research literature to their project.		✓	✓
S9	applies critical thinking in the research process.			✓
S10	demonstrates capability in formulating research questions answerable with data.		✓	✓
S11	demonstrates understanding of sound methodological procedures when setting up experimental work.	✓	✓	✓
S12	demonstrates knowledge or understanding of data analysis procedures.		✓	✓
S13	contributes own creative ideas to the project.		✓	✓
S14	can identify and articulate limitations in research design.		✓	✓
S15	is adept at problem-solving.		✓	✓
S16	is capable of linking theory with empirical work.			✓
S17	prepares effective scholarly presentation materials.	✓	✓	
S18	demonstrates adequate scholarly presentation skills.	✓	✓	
S19	demonstrates adequate scholarly writing skills.	✓		
S20	I can count on the student to meet scheduled commitments.		✓	✓
S21	gives advance notice if unable to keep scheduled tasks or appointments.	✓	✓	
S22	Overall, the student has good time management skills.		✓	
S23	Overall, the student is very dependable.		✓	✓
S24	shows genuine interest in the research project and process.		✓	
S25	takes ownership of the project.		✓	✓
S26	When the student 'gets stuck', she/he seeks paths forward by own initiative.		✓	✓
S27	conducts her/himself in a professional manner in face-to-face interactions.		✓	
S28	conducts her/himself in a professional manner in email correspondence.		✓	
S29	is capable of discussing scholarly concepts with team members.		✓	
S30	is respectful to different points of view.		✓	✓
S31	has the ability to make independent progress between mentor/team meetings.			
S32	contributes to a motivating research team experience.		✓	
S33	demonstrates thoughtfulness in making own decisions or seeking support for evolving directions of the project.		✓	
	Total number of questions for which average ratings increased across mentor assessments	6	28	19

2.6 E3: Faculty-assessed Student Outcomes and Benefits (Post Measure)

Faculty mentors individually completed a survey released immediately after the program ended. Faculty assessed student outcomes (*my students were able to make progress on working independently; my students were able to work on the project we identified for her/him in the way we envisioned*), as well as benefits for students of the early research experience in terms of scientific identity (*program helped students become better researchers; program gave my students a realistic understanding of life as a researcher*) or career aspirations (*program will help my students be more successful in graduate study; program helped my students develop career paths*). We computed the proportion of faculty that *strongly agreed* with corresponding statements.

2.7 E4: Student-led Disseminated Products (Post Measure)

As a loosely relevant objective measure, we tracked research dissemination outcomes: number of accepted refereed team publications at professional venues, number of students as lead author of publications, and number of student presentations about the research. While not directly reflecting perceptions of belonging, research products can be viewed as an objective validator and as overt recognition of belonging to the research community of practice. Presenting research on behalf of their teams can provide students with opportunities to network toward graduate school and research careers; such formative networking was identified as important by Shanahan et al. [45].

2.8 E5: Alumni-assessed Career Aspirations and Progression (Extended Post Measure)

We conducted an alumni survey which gathered facts and anecdotes of post-program activities in both structured and unstructured answer formats. Program alumni (former students) were invited back to complete the survey anonymously. This resulted in 39 individual responses over the three years such that 2016 participants (43.5% of total 39 responses) had three opportunities to complete the alumni survey, 2017 (43.5% of responses) had two opportunities, and 2018 (13% of responses) had one opportunity. Alumni provided information on career progression and engagement in scholarship dissemination. The survey was administered at a point after which graduate school applications would have been submitted and application decisions received. We computed the percent of total responses. Qualitative data from alumni's open-ended comments was also considered.

3 RESULTS

We used the multicomponent framework introduced in the prior section to report on results of the training intervention per three hypotheses about the development of scientific skills, scientific identity, and aspirations for research career. Given the sample size, we focused on descriptive measures and trends as well as qualitative discussion of open-ended answers.

3.1 E1 Results

The right-most three columns of Table 2 indicate per year the skills for which average ratings continuously improved over three assessments. Skills not indicated were assessed on average as having a flat or decreasing rating for at least one of the three assessments.

The research methodology skill (S11) had a continuous increase in all years, highlighting that the intervention supported its steadfast development. Several disciplinary and broader scientific skills also showed a continuous increase in ratings in two of the three years: S1 (computer programming), S2 (resourcefulness), S3 (new software), S4 (new hardware), S7 (technical/scientific literature), S8 (research literature), S10 (formulating research questions), S12 (data analysis), S13 (creative ideas), S14 (research design limitations), S15 (problem-solving), S17 (presentations preparation), S18 (presenting), S20 (accountability), S21 (notifying), S23 (dependability), S25 (taking ownership), S26 (initiative-taking), and S30 (respectfulness). The last two cohort years indicated a more pronounced improvement trend, applicable to 19 or 28 of the assessed skills.

In contrast, skills related to communication (S27–S29) or to other scholarly skills (S5 — initiative taking; S6 — eagerness to explore unknowns; S9 — application of critical thinking; S16 — ability to connect theory and empiricism; S19 — scholarly writing; S22 — time management; S24 — genuine interest; S31 — independence; S32 — motivating a research team; S33 — thoughtful decision-making) did not show as consistent improvement.

3.2 E2 Results

As seen in Figure 5, pre and post comparison of student self-assessed scientific skills showed gain for, especially: *formulating research questions*, *developing a research plan*, *data collection and human subjects considerations*, *data processing*, *understanding and critiquing research literature*, *research ethics*, and *preparing spoken and written research dissemination*. In contrast, two skills were self-assessed as declining in one year: *grant writing* in Y3 and *programming and application/system development* in Y1. In addition, Figure 6 reveals that students, when completing the post survey, perceived that their abilities generally increased, and especially in Y3. For instance, in Y3, 100% felt that they improved their *ability to critique research literature*, *ability to analyze data and interpret results*, *skills to effectively disseminate findings*, knowledge of *tools and techniques in the field*, and their *tolerance for obstacles in the research process* either *somewhat* or *to a great extent*. In terms of development of scientific identity, a majority of students reported gains in *increased academic self-confidence* and *understanding how researchers think and work on problems*. In addition, there were gains for *increased confidence in potential for academic career* and *readiness for more demanding research*, relating to research career aspirations and career progression. Additionally, results for summative metrics about career intent are in Table 3. Most participating students intended to pursue graduate study and the majority in STEM fields.

3.3 E3 Results

Figure 7 shows that faculty felt the intervention contributed to student development, although with a lower proportion of *strongly agree* in one year. Faculty also identified benefits for students in terms of developing scientific identity and positive career aspirations toward the scientific profession. For career aspirations, responses affirmed stronger benefit for preparation for graduate school than for careers in research generally. On average, faculty above all indicated they *strongly agreed* that the program *will make students more successful in graduate study* (i.e., research career aspirations and progression), and that the experience helped students *become better researchers* (i.e., scientific identity). The lowest average proportion of *strongly agreed* among faculty respondents was for *gave my students a realistic understanding of life as a researcher* (scientific identity) and *helped my students develop career paths* (research career aspirations and progression).

Table 3: Students' self-reported intent to pursue graduate school (n = 10 annually; 30 total).

Evidence from student evaluation	Y1	Y2	Y3	Mean
1. Intend to pursue grad school in STEM	50%	80%	70%	67%
2. Intend to pursue grad school in non-STEM	30%	10%	10%	17%

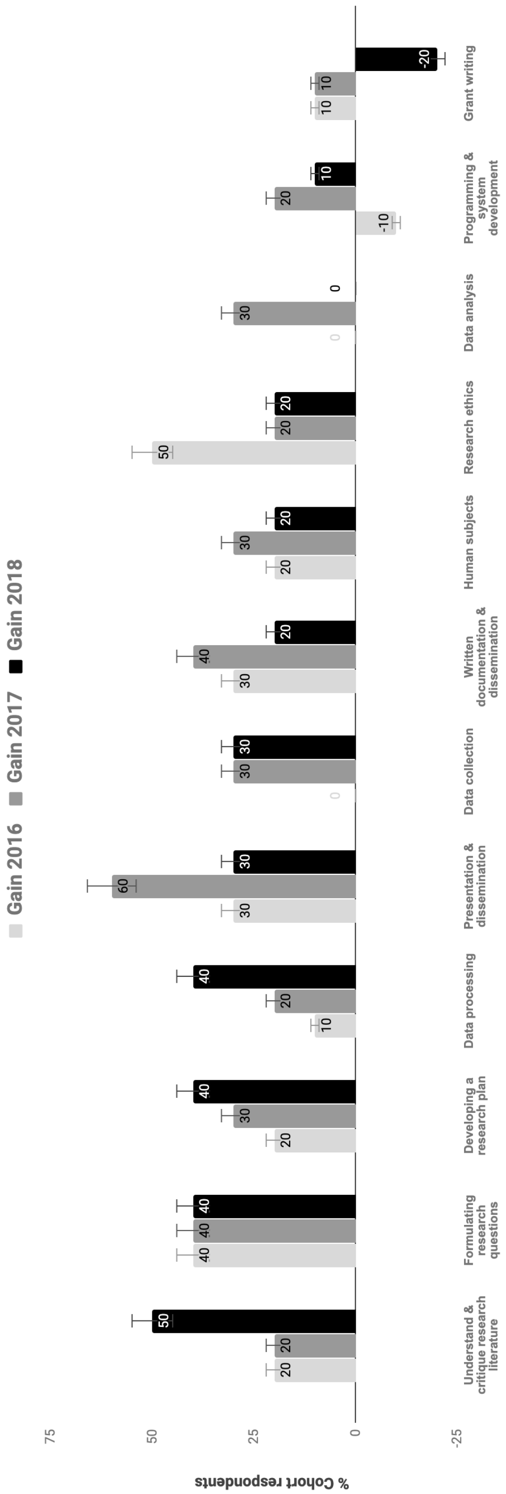


Figure 5: For all three years, students' self-assessment of their skills show cohort gains in most skills in pre and post program comparison. Gain was computed as the difference between the post and pre upper-end skill ratings. (Proportion of n = 10 annually; 30 total; Y2 and Y3 had 9 post responses.)

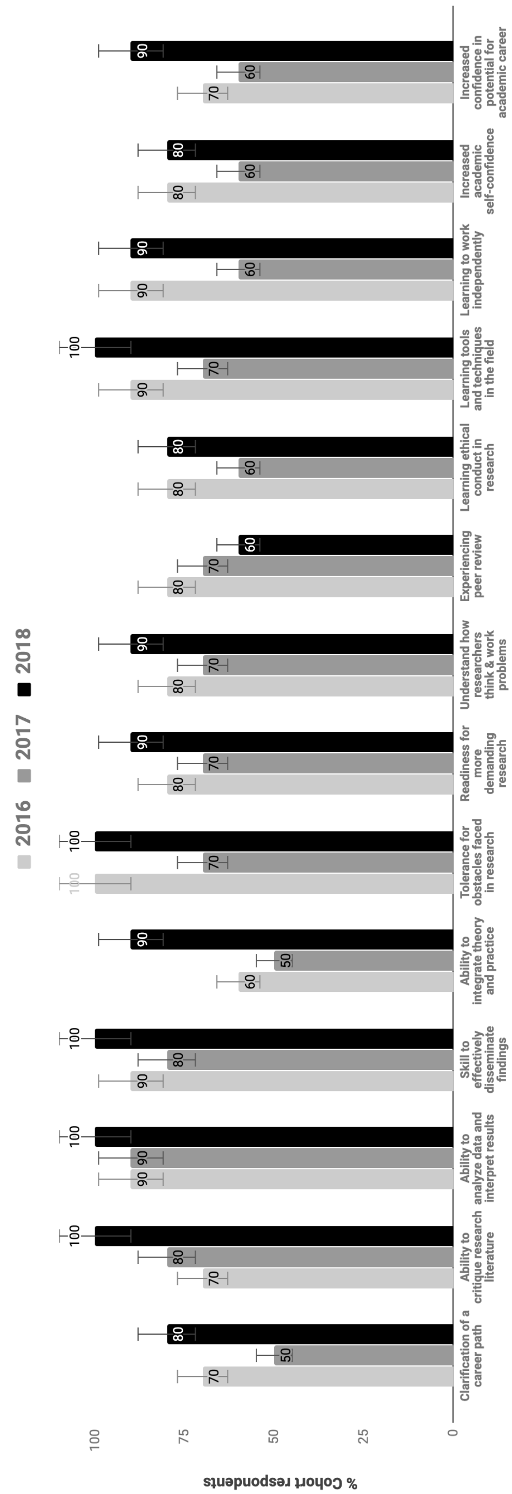


Figure 6: For all three years responses from the student post-program survey shows that the majority of student cohorts perceived gains in skills *somewhat* to *a great extent* in many areas. (Proportion of n = 10 annually; 30 total).

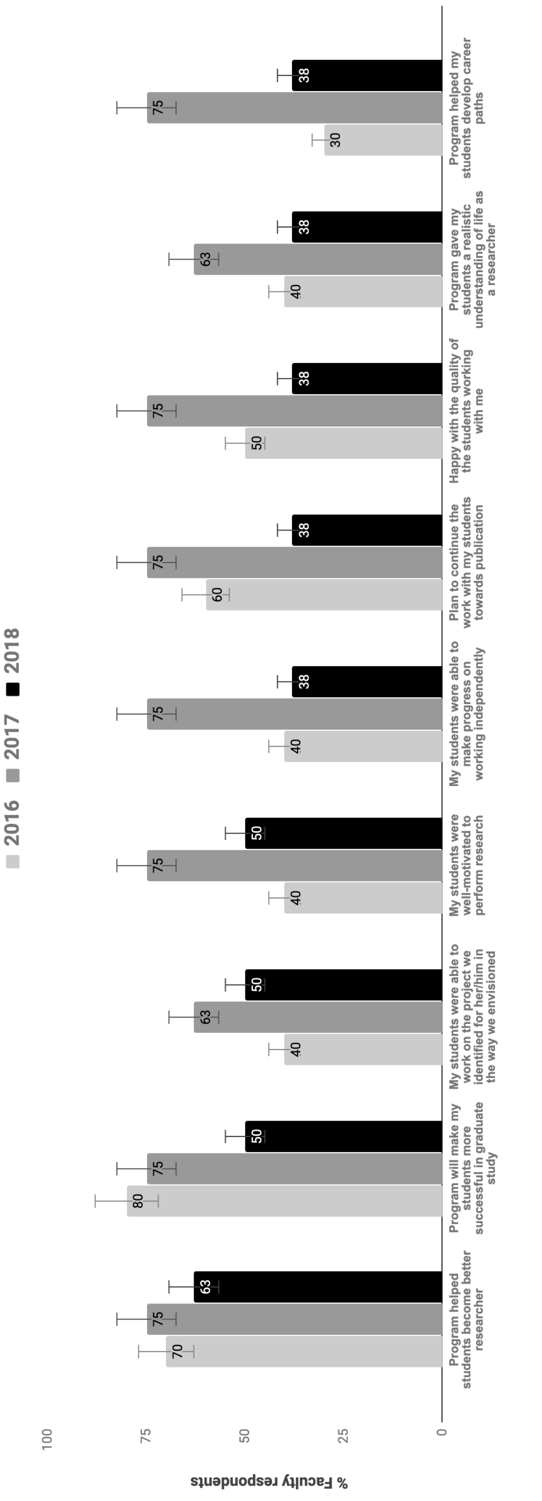


Figure 7: Many faculty *strongly agreed* with statements about student benefits across the three years; others generally *agreed*. (Proportion of n = 10 in Y1 vs. n = 8 in Y2 to Y3.)

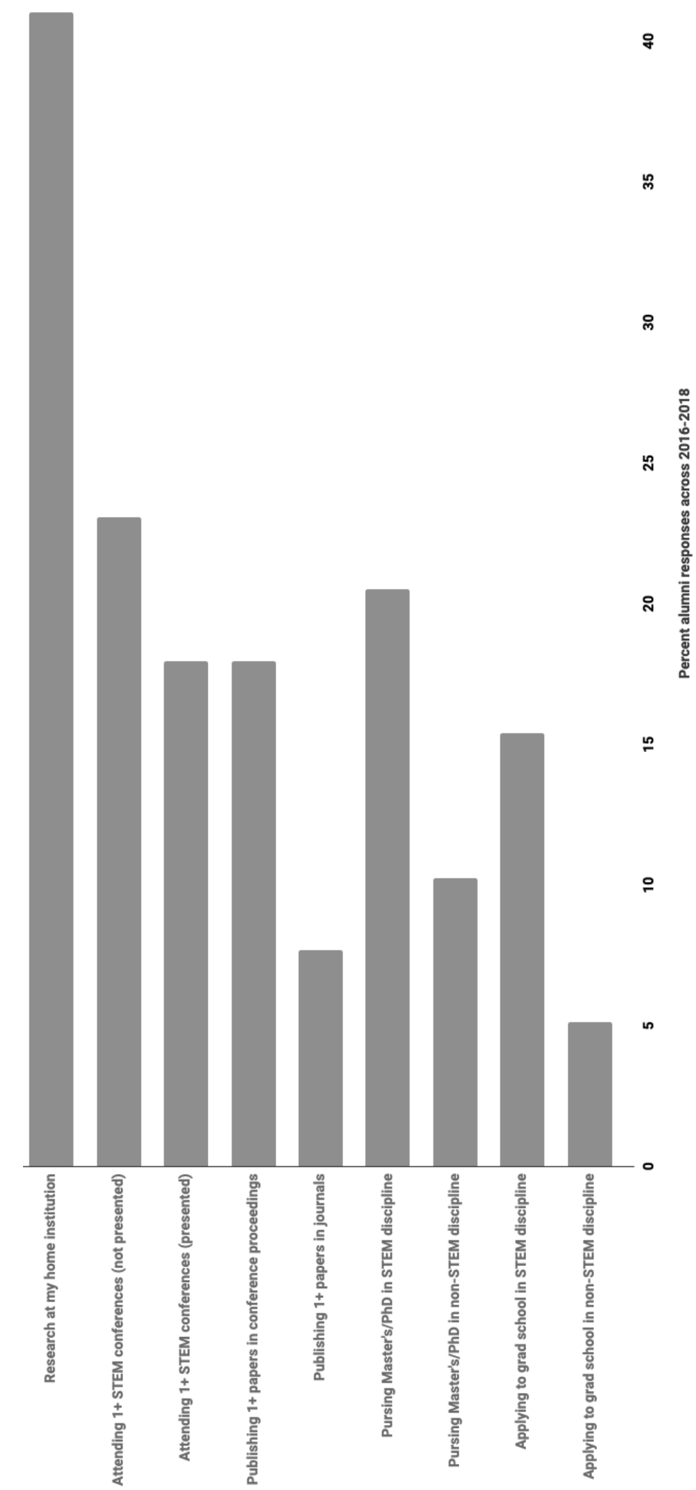


Figure 8: Percent program alumni responses self-reporting career and activities choices for three years (n = 39 total responses). 1+ = one or many.

3.4 E4 Results

The research projects placed computational sensing in the center of a research experience, translating into refereed dissemination of research discoveries, including eleven refereed technical team publications with students as lead authors [8, 17, 21, 23, 31, 35, 40, 42, 43, 50, 53], and two other student-led technical publications [6, 15]. There were additionally 30 pre-publication student-presented talks or posters at a local undergraduate research event, as well as annual pre-publication posters at a national undergraduate research symposium.

3.5 E5 Results

Aggregated results of alumni surveys over the three years are in Figure 8. Students continued to *engage in research after returning to their home institution*. In addition, of the responses, almost a fifth reported they *presented research at a STEM conference* and/or *published a conference proceedings paper*. Over one fifth of the responses also indicated that respondents were *attending graduate school in STEM disciplines*, and/or that respondents *applied or intended to apply to graduate school in a STEM discipline*. Graduate program aspirations included computer science, human-computer interaction or human factors, robotics, computational physics, psychology, game design and development, mathematics, computer engineering or other engineering disciplines.

Additional open-ended comments about recent activities or career plans indicated impact of the research experience for future career visions in computer science and STEM disciplines:

> *[This] program was mentioned in all of my formal and informal interviews for grad school, so I give it a lot of credit for helping me achieve my educational goals.*

> *If it weren't for [this program] and my mentors, I may never have considered applying to get my MS, and my short term career prospects may have been very different.*

> *I was accepted to 2 PhD programs and took a position in [program] at [university]. I started in August, and my research focuses primarily on perception-action and robotics with funding from [organization], technology use and design for people with Autism Spectrum Disorders, and cybersecurity. I've completed one semester, going on two, with research submitted for publication with multiple Human Factors-related conferences and journals.*

> *I intend to earn a PhD in Computer Science and then see where that takes me. I might try to become a professor some day.*

> *I attended [conference], the yearly conference of the [organization], where I attended various career building sessions and got an internship offer from [organization]. In addition, I travelled to IEEE [conference] with my research partner to present our research from our summer [program]. Outside of STEM pursuits, I have resumed a job writing for my school's newspaper ...*

> *Obtain a PhD in Computer or Mechanical Engineering.*

> *I am fairly set on pursuing a PhD after finishing undergrad, although I'm not sure if I want to ultimately go into industry or academia. I am interested in AI for robotics or medical applications and computational physics, and I will probably end up pursuing my PhD research in one of those areas.*

> *... I attended the Grace Hopper [women in computing] conference on a full scholarship, presented research at the [...] Symposium, and completed my computer science degree. Currently I am in a fully-funded machine learning bootcamp program organized by [organization].*

4 DISCUSSION

We reported on the impact of an early research experience for diverse cohorts of undergraduates in computing for growing scientific skills, increasing science identities, and fostering career aspirations. Figure 9 integrates results from all forms of evidence in our evaluation framework. They indicated the benefits of the intervention.

For hypothesis (a), evidence from faculty assessments of students and student self-assessments (E1, E2) indicated that the intervention resulted in gains in scientific skills. That communication and abstract skills were not reported to consistently improve may reflect that extended practice is required to develop them. Moreover, the difference in Table 2 from Y1 compared to Y2–Y3 in the number of consistently improving skills may reflect adjustments made in response to student/faculty feedback in the training schedule, including in front-loading the schedule of professional development activities in the experience which appeared to have better supported skills development.

For hypothesis (b), evidence from students and faculty (E2, E3) indicated that the early scientific experience contributed to scientific identity development. Additionally, the dissemination data (E4) arguably represented a tangible recognition of belonging to the scientific community. That faculty rated students' development of a realistic understanding of research lower may relate to the compressed timeframe of the intervention and that a 10-week research project is not reflective of the typical duration of graduate research projects.

As regards hypothesis (c), evidence from faculty (E3) suggested that the intervention nurtured scientific career progression, especially in terms of preparing students for graduate school, the next step in their careers. Considering the SCCT theoretical framework [32], the majority of students indicated an intent to pursue graduate school in STEM (E2) and also a confidence boost about their capacity for an academic career. These were indicators that the program promoted scientific career aspirations, as were alumni

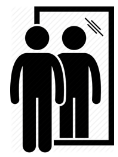
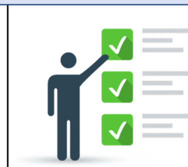
Five Forms of Evidence				
				
E1 Faculty-assessed student skills *repeated in-program measures*	E2 Student self-assessed skills and benefits *pre and post measures*	E3 Faculty-assessed student outcomes and benefits *post measure*	E4 Student-led disseminated products *post measure*	E5 Alumni-assessed career aspirations and progression *extended post measure*
Key Findings				
There was a rising trend in faculty-assessed student skills over ten weeks, in Y2 and Y3. Skills related to communication or abstract scholarly skills did not show as consistent an improvement.	Most participating students reported plans to pursue graduate study in STEM fields. Students reported gains in scientific skills, science identity, and research career aspirations.	Faculty felt that the experience positively impacted student growth. Faculty confirmed that the experience benefited students' preparation for graduate study.	The intervention resulted in refereed dissemination with most students as lead authors. Students presented research at local, national, and international venues.	Many students continued to engage in research after the program. Close to one-third have commenced or been accepted to PhD programs. Others have continued to Masters.

Figure 9: Overview of evaluation framework components and key findings. A comprehensive multicomponent evaluation framework is adopted to avoid pitfalls associated with self-reporting alone.

responses about planned applications or confirmed acceptances to graduate school. Additional post-contact with alumni completes the picture for hypothesis (c). Approximately a third have already continued on to PhD programs in STEM, and additional students to Master's programs. Alumni have, in particular, placed into graduate programs in computer science or closely related fields, such as degree programs with an interdisciplinary computing focus.

In addition, regarding the need for increasing diversity in computing and in other STEM fields, comments from students in the diverse cohorts acknowledged the importance of diversity and inclusion in the practice of research:

> *Diversity is vital, particularly when the research involves human subjects, because human populations are diverse. The researchers should reflect their work. Additionally, diversity allows for unique experiences and thus ideas and viewpoints.*

> *Diversity can help prevent implicit biases that may be held by a particular group without them even realizing it.*

> *[H]aving a range of perspectives overseeing a project is essential for the best possible outcome.*

> *[Diversity is] very important. It's always nice to see someone who looks like you or have a similar upbringing in the same field of study, especially computer science. Diversity is also important because it allows for different perspectives to be brought to a project or research assignment.*

> *I feel that having a variety of experiences and backgrounds always helps any project, whether in research or otherwise. To this extent, diversity is extremely important as it creates the opportunity for a wealth of ideas and viewpoints to be expressed. Additionally, I believe that people do their best work when they are in an environment they feel welcome in, and having diverse mentors and peers supports this.*

Revisiting the cognitive apprenticeship framework discussed earlier, these comments further emphasize the link between effective apprenticeship and coaching with inclusive mentoring environments, and they highlight the importance of collaborative diversity in research teams. That students recognize the discipline's challenges and its present limitations in diversity, equity, and inclusion can also be regarded as an indicator of their growing connection and self-identification with the field.

5 CONCLUSION

We reported on and discussed an intervention that provided diverse student cohorts with a computer science-focused early scientific experience. Integrating multiple sources of evidence supported that the intervention helped develop scientific skills and identity, in addition to nurturing research career aspirations and progression. Several participants have already continued on to PhD programs in computer science or STEM. Targeted recruitment outside of the US Northeast may improve geographic diversity of participants. The introduced intervention—see overviews in Figures 2, 3, and 4, and the Appendix—is applicable in other disciplines and institutional settings. Resource needs would primarily include cost and time involved. For example, in the reported study, students received internship stipends, subsistence, and travel support; and the organizers and faculty of the training intervention invested their time before, during, and after the 10-week experience. In future work, we are interested in studying potential long-term implications for undergraduate researchers who publish the results of their research and subsequently pursue a research profession, including topics such as downstream research career productivity and the mentoring practices they adopt as research professionals.

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A APPENDIX: OVERVIEW OF PROFESSIONAL DEVELOPMENT PROGRAMMING

- *Workshops:* Students attended workshops on research-relevant topics such as human subject research, statistics, data visualization and research storytelling. (Figure 3: A).
- *Toward Graduate Studies:* Students developed understanding about graduate school or initial grant writing skills for graduate school, a new topic to most participants. We focused on a national program for graduate fellows and students also met a panel of prior recipients (Figure 3: B).
- *Public STEM Outreach:* Students presented a hands-on exhibit of various sensing technologies at a local public library, interacting with library patrons of all ages (Figure 3: C).
- *Coordinated Interdisciplinary Events:* The organizers coordinated interdisciplinary joint activities with nearby programs that were both social and academic in nature, including a graduate study and research symposium featuring sessions with research talks by doctoral candidates for insight into PhD-level STEM research, and panels about graduate school (Figure 3: D).
- *Journal Club:* Students discussed papers within the scope of the program's intellectual theme. Written and oral reflection

exercises coached critical scholarly reading and technical writing.
- *Industry Research Lab Visit:* Students visited an industrial research lab as part of having them consider a range of research career paths. At this visit, students interacted with professionals and received feedback on their project-in-progress.
- *Observing a PhD Defense:* Students were encouraged to attend a PhD dissertation defense.
- *Teaching-to-Mentoring Bridge:* In talks, mentors shared about their research journey and discussed topics of expertise of relevance to the program's intellectual focus such as: *Facial expressions in VR and affective computing*, *Visual perception and what we learn from eye tracking*, *Linguistic sensing and computers making linguistic sense*, and *Intelligent systems that learn deeply.*
- *Post-program Sessions:* In video get-togethers, organizers reconnected with the cohort and let alumni share about their progress and activities at home institutions (Figure 3: E).