Equitable Student Persistence in Computing Research Through Distributed Career Mentorship

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ABSTRACT

Google's CS Research Mentorship Program (CSRMP) cultivates pursuit and persistence in the computing research trajectory for students from historically marginalized groups through virtual career mentorship from industry professionals, a peer community, and just-in-time resources. Since 2018, 287 Google mentors have engaged 1,018 students from 247 institutions in the U.S. and Canada. The program employs socioemotional support and advocacy to navigate systemic barriers by validating students' intersectional identities in order to improve outcomes in core constructs for students: self-efficacy, sense of belonging, research skills, motivation to pursue graduate school and research careers, and intersectional capital. Evaluation outcomes from 400 matched respondents (68% response rate) indicate that CSRMP affects positive, statistically significant change in those constructs that largely persists across demographic subgroups. 80% aim to pursue computing research careers, and significantly fewer students are undecided about their future career. We were also able to identify disaggregated learnings: Black, Indigenous, and Latinx students are significantly less likely to submit to a research conference, and students from Historically Marginalized Groups (defined within) are significantly less likely to apply to a CS graduate program. We discuss key design elements of the program, how the findings are informing future iterations, and the potential for the model to scale.

CCS CONCEPTS

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

KEYWORDS

computing, research, graduate school, mentorship, equity, capital, intersectionality

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1 INTRODUCTION

Systemic and social barriers in CS education have marginalized students from certain identities, leading to their underrepresentation in advanced degrees and research. In the U.S. and Canada in 2021, resident students who identified as women, nonbinary, American Indian/Alaska Native, Black/African-American, Native Hawaiian/Pacific Islander, Multiracial (not Hispanic), or Hispanic represented 26% of CS Bachelor's degrees awarded at PhD-granting institutions, but barely 12% of PhD enrollments [43]. Of 78 responding departments, 1% of PhD students received disability accommodations; 72 departments responded that 19% of their enrolled students identify as first generation college students [43].

There are many systemic barriers to CS research for students from marginalized gender/racial/ethnic identities and disability/socioeconomic statuses (hereafter, marginalized students). Only 51% of U.S. high schools offer foundational CS courses, and those schools are more likely to serve suburban, higher socioeconomic status (SES) student populations who identify as Asian and white [8]. Being the first in their family to engage with CS, research, and/or higher education determines a student's preparatory privilege, or the amount of knowledge and confidence they have to navigate a certain environment or field [19].

The meritocracy prevalent in higher education rewards preparatory privilege, and is a barrier to equitable participation in CS and research [19]. In one study, CS accounted for 16% of foundational undergraduate STEM courses where more than 20% of students who withdrew or received a D, F, or incomplete course grade, decreasing their likelihood to return to the subject or institution the following year, were disproportionately likely to be marginalized students [41]. Further, central scientific processes are fundamentally biased: women receive fewer attributions on articles and patents [29] and significantly lower scores on research funding proposals, despite blinded review, due to word choice [18]. Marginalized students face social barriers when in CS environments, which are largely shaped by the dominant culture of affluent Asian and white males [11, 22], such as discrimination, stereotypes, alienation, and few peers who share their experiences and values [7, 8, 24, 38].

Google's CS Research Mentorship Program (CSRMP) was designed to increase the pursuit and persistence in graduate school and computing research for marginalized students by positively impacting five key constructs: self-efficacy, sense of belonging, actionable skills, motivation to pursue graduate school and research, and research capital [4, 15, 21, 26, 30, 31]. We posited that receiving career mentorship in CS research that is responsive to students' intersectional identities and experiences, without being tied to a research project, can improve outcomes in these constructs.

2 RELATED WORK

Experiences in research can significantly increase the likelihood that marginalized students pursue and persist in graduate and professional education [2, 10, 13, 34] and careers in academia [36]. Student participants of an introductory, academic-year-long, team-based CS research project had significantly higher sense of belonging, greater pursuit of additional research (57% vs 39%) and greater interest in applying to graduate school (83% vs 24%) than other CS majors at the institution [1]. Analysis of 58 undergraduate CS research sites found that students from marginalized ethnicities had significantly higher CS self-efficacy, academic help-seeking/coping, research skills and scientific leadership [28].

Once in graduate school, students with a mentor report higher self-efficacy in their computing career track than those without a mentor [35], and quality mentoring relationships increase students' number of publications, working relationships with advisors, and satisfaction with graduate school overall [9, 37]. One study of formal CS research experiences for first-year students showed that when mentor support is low, sense of belonging is significantly lower for women and/or Black, Hispanic and multiracial students than for Asian and white men, but the belonging gap disappears when mentor support is high [33]. CS research interventions produce positive outcomes when they include culturally and personally relevant content with societal impact [14, 17, 28], and a community of peers and near-peer mentors [23, 32].

The National Academy of Sciences outlines that effective mentorship is culturally responsive, "provides aspects of both psychosocial and career support, and may include role modeling, advising, sponsorship, and helping the mentee develop a supportive network of other mentors and peers" [5, p.13]. Trust must account for power dynamics that exist across lines of difference [39] between mentor and mentee identities. Many mentoring relationships begin with a focus on instrumental (e.g. learning tools/processes, goal setting, feedback) and networking support, but Tenenbaum et al. found that socioemotional support is what significantly increased students' satisfaction with their advisors and graduate programs [37]. Socioemotional support takes the form of encouragement, empathy, and role modeling; sharing the mentor's personal and professional life experiences and validating those of the mentee. Departments that engage in socioemotional mentoring send larger portions of their undergraduate seniors to graduate school, regardless of student achievement [9]. Additional components of socioemotional support that positively impact students include growth mindset (that abilities can be developed through effort and persistence rather than inherent talent) [12], asset thinking (recognition of one's unique, existing capabilities rather than what they lack) [16], operating with cultural competence [40] and normalizing failure [26].

Intersectional Capital is a culturally-responsive framework that describes "a set of environmental and interpersonal conditions that enable students [...] to pursue STEM and computing by validating and leveraging their multiple, interlocking identities as assets" to their professional development [31, p. 3]. Rather than requiring individuals to assimilate to the culture of CS defined by dominant group Asian and white males, they are encouraged to participate with the full authenticity of their unique lived experiences [15]. Mentors and peers cultivate Intersectional Capital through open discussion of successes, challenges, questions, and how one's personal values relate to the technical domain. Relationships established within Intersectional Capital help students acquire social and scientific capital (e.g. advocates/sponsors) that values their identities.

3 PROGRAM DESIGN

CSRMP aims to increase the number of students who identify as women, nonbinary, Black, Indigenous, Latinx and/or students with disabilities pursuing graduate studies and research careers in CS by matching them with peers and a Google mentor to focus on a career development topic and a focused research area. Scaling from a 1:1, 12-month mentorship model with 15 students during its 2018 inception, the program now uses a 1:3 mentor to student model, accepting up to 300 applicants per cycle and running two fully virtual, 12-week cycles per academic year (January-April, September-December). Since 2018, 287 Google mentors have engaged 1,018 students from 247 institutions in the U.S. and Canada.

Outreach and recruitment To recruit mentors, CSRMP utilizes an internal communications strategy (i.e. within Google). The initial call for mentors is sent to Googlers with backgrounds in research and to employee resource groups. It is then amplified by leadership and marketed across internal platforms and newsletters.

CSRMP conducts targeted outreach to students both internally and externally. The opening of applications is announced internally via the same methods for mentor recruitment. It is also announced in external blog and social media posts highlighting the program experience of and impact on a past student. CSRMP then shares a social media kit and email templates with program alumni and a contact list that includes internal and external stakeholders, higher education faculty, administrators and staff, partner organizations, and affiliates who may help spread the word.

Application and review Students must be actively enrolled in an undergraduate or graduate degree-granting program, including community colleges, in CS (or an adjacent field) in the United States or Canada for the full duration of the mentorship cycle, and have a minimum cumulative GPA of 2.5 on a four-point (or equivalent) scale. Given that participating in the culture of CS research shows statistically significant improvements for first and second year undergraduates [1, 33, 42], the program is designed to be interest-based, open to students with no prior research experience, rather than merit-based. Students to submit a personal statement covering: their interests, experiences, and motivations in computing; how participating in the program would contribute to their long and short-term computing research goals; and how their lived experiences would enable them to add value to their peer community and have a unique impact on society through computing research.

Submitted applications are randomly assigned three blind reviewers to evaluate the following criteria: Research interests (describing their computing research interests and rationale), Motivation (outlining actionable goals for their computing research pathway), Readiness (critical thinking about what they would like to gain from and contribute to the program), and Impact (reflecting on their unique perspectives and opportunities to leverage them for positive impact through computing research). All students who score above a certain score threshold are eligible for matching.

Selection and matching In the application, students indicate their Education Level as undergraduate or graduate, select primary and secondary Research Areas, and select one of the following Career Topics to work toward in the program: Introduction to research pathways, Defining a research problem, Applying to graduate school, Navigating the publication process, or Applying to a postdoc/academia/industry position. During the mentor application, mentors select up to two Education Levels, three Research Areas, and five Career Topics they can support.

Each mentor is then matched to three students, forming a small group mentorship "pod" that allows students to connect with peers of similar interests. Match assignments are first made via a combinatorial optimization algorithm such that all pod members (mentor and students) share a Topic to align on appropriate goals and activities and all pod students share at least one Research Area with the mentor. Matches are manually reviewed to optimize the number of students accepted and the fidelity of Topic and Research Area alignment within a pod. Matched students and mentors are accepted; those who are unmatched are declined from the program cycle and eligible to reapply in the future.

Training Mentors attend an orientation to gain an understanding of: the current state of representation in CS research, the program's mentorship method, and the value-add of their mentorship; effective strategies to champion their mentees' career development; competency for inclusive leadership across lines of difference; and additional resources and next steps.

The program's mentorship model is directly informed by the interventions and concepts in Section 2, and employs Tenenbaum et al.'s three types of support (networking, instrumental, socioemotional) [37]. Within networking support, mentors are encouraged to connect students to people, knowledge, and opportunities in CS research. Resources are provided for instrumental support to help mentors structure 1:1 meetings focused on actionable progress with students, and provide thoughtful, objective feedback. Within socioemotional support, mentor training discusses growth mindset, asset thinking, psychological safety, and imposter phenomenon. Mentors are provided with prompts to promote intersectional capital, personal connection and empathy, mentee-driven interactions, cultural competence, and discussions across lines of difference. Finally, the training provides mentors an opportunity to reflect on themes regarding their personal experiences with mentorship, psychological safety, and socialization in CS. The student orientation covers many of the same topics and frameworks, introduces the program team, and sets expectations for participation and communication.

Engagement Mentors provide general career mentorship to students, but they do not direct student research projects or publications. Over twelve weeks, mentors are expected to engage with students via two core activities: three monthly pod sessions to collaborate on goals, build community, and hear diverse perspectives, and four 1:1 sessions to engage, validate and support each mentee personally. Mentors and students are given an activity guide, discussion prompts and resources that can be used to structure sessions around goal setting, career planning, and resources specific to the Career Topic of the pod.

Mentors are encouraged to engage with each other through an asynchronous chat and synchronous discussions on best practices, successes, and challenges. In addition to participating in pod and 1:1 sessions, students attend Full Group sessions of career panels, tech talks, personal and professional development workshops, and community-building activities from a variety of program alumni, Google researchers, and subject matter experts.

To help the program team gauge whether activities are proceeding as planned, user experiences are positive, and what additional support is needed to enhance the program, both students and mentors are expected to complete bi-weekly polls in addition to pre- and post-surveys, and encouraged to attend office hours as needed. Poll responses are reviewed as a formative check-in of the user experience, with the program team intervening for any struggling students or mentors. The program team shares a weekly newsletter with program updates, upcoming research conferences, scholarships and opportunities, and other relevant content as requested (e.g. activities to encourage connection among students, innovative and creative applications of CS research for real-world impact, alumni spotlights to highlight near-peers' career paths).

4 METHODS

A repeated measures survey design research methodology was deployed, with student participants from both 2021 cohorts invited to take a pre-survey within 2 weeks of program orientation and a post-survey within 2 weeks of the program close. The survey instrument was adapted [27] to measure the key outcomes intended for the program: Confidence (7 self-efficacy items), Community (6 sense of belonging items), Skills (9 research skill items), Motivation to pursue computing (2 academic and career plans multiple choice items), and Intersectional Capital (8 items) that we developed from a previous qualitative study [31]. Overall program quality was measured at post-survey via mentoring (9 items), peer mentoring (9 items), and general program feedback (7 items). Items were rated on five-point Likert scales from 1 (Strongly disagree) to 5 (Strongly agree). Reliability coefficients (Cronbach's alpha) were at .86 and above for each scale. Additionally, demographic items asked participants to identify personal contexts such as gender, race/ethnicity, ability and being the first person in their family to attend college. The post-survey included a single item of what academic- and career-related next steps students planned to take after the program (e.g. apply for an internship, apply for graduate school), as well as qualitative items that are outside the scope of this study.

We built five composite demographic subgroups to investigate outcome patterns across student identities. **Historically Marginalized Group (HMG):** respondent identifies with one or more of the following: Black/African descent, Hispanic/Latino/Latinx, Indigenous, Middle Eastern/North African; Mental health/neurodiversity condition, Physical disability; Nonbinary, Woman. **Black/ Indigenous/Latinx (BIL):** respondent identifies with one or more of the following: Black/African descent, Hispanic/Latino/Latinx, Indigenous. **Black/Indigenous/Latinx nonbinary and women (BILNW):** respondent identifies with: Black/African descent, Hispanic/Latino/Latinx, and/or Indigenous *AND* Nonbinary and/or Woman. **First Generation (FG):** respondent indicates they are the first in their immediate family to attend college. **Students With Disabilities (SWD):** respondent indicates they have a physical disability or mental health/neurodiversity condition. These subgroups overlap and are not discrete respondent groups, because of the multidimensionality of identity [20]. These subgroups have been constructed as a means to understand the experience of program participants from within their multiple identity contexts, a recommended analytical approach [20].

The survey responses were analyzed using both independent and paired *t-tests*, with independent and paired *t-tests* run for each of the five demographic subgroups to ensure equitable outcome patterns across participants' identity grouping. Outcome patterns are observed, but not compared statistically between subgroups because the subgroups are not mutually exclusive, and because of the inherent methodological problems of intersectional identity quantitative studies, often referred to as the 'additive assumption' [3]. For example, comparing groups statistically that are based upon intersectional identity forces the analysis to treat respondents as their gender plus their race/ethnicity, rather than examine the nuances of how these identities are intertwined. Comparing groups in this way can statistically support an implicit deficit model approach. Our theoretical foundations inform this program evaluation in that we recognize that systemic oppression exists and influences how students experience a program designed to support them. For the purposes of program evaluation we seek to understand how students in the program were impacted and what nuances might exist among intersectional identity groups. The construct scales and identity subgroup pattern analysis protocol are shared with other Google programs that support students in CS research (exploreCSR, PhD Fellowships) to view differences in outcomes across our programs designed to address diversity, inclusion and equity in the field.

The evaluation questions guiding this study of intersectional populations are: *1) What change does CSRMP affect for students in key constructs known to predict pursuit and persistence in CS research? 2) How does that change translate across demographic subgroups?* Because they represent more rigorous findings, we report paired *t-test* results from matched participant samples. A McNemar test was used to observe response changes for academic and career plans pre-to-post. Subgroup patterns for actions taken following the program were compared by *chi-square*.

5 RESULTS

Two program cohorts from 2021 were combined into a single sample. A total of 590 participants were invited to participate in the pre- and post-survey. We were able to match responses from 400 participants (68% response rate). 68% of respondents were pursuing undergraduate degrees, with 18% pursuing Masters' degrees, and 20% pursuing doctorate degrees (including some in dual-enrollment programs). The demographic subgroups were identified from post-survey responses. Gender, race/ethnicity and disability status allowed for multiple selections. The HMG subgroup contained 217 participants (54%), the BIL subgroup contained 99 participants (25%), the BILNW subgroup contained 38 participants (10%), the FG subgroup contained 106 participants (26%), and the SWD subgroup contained 42 students (11%) (see Table 4).

Table 1: Paired t-test pre-to-post student survey outcomes

Construct	Pre-survey (n = 400) Mean (SD)	Post-survey (n = 400) Mean (SD)	Significance (p)	Effect size (Cohen's d)
Confidence	4.05 (0.71)	4.37 (0.65)	<.001	0.92
Skills	3.31 (0.79)	4.05 (0.71)	<.001	0.91
Community	3.72 (0.77)	4.16 (0.74)	<.001	0.87
Capital	3.45 (0.75)	4.17 (0.70)	<.001	0.86
Mentoring	-	4.31 (0.78)	-	0.93
Peer Pods	-	4.05 (0.92)	-	0.94
Program	-	4.31 (0.78)	-	0.94

All survey construct means improved significantly at post-survey. Table 1 presents the construct means, standard deviations, significance, reliability and effect sizes. Mentoring, peer mentoring, and overall program ratings were assessed at post-survey. Students indicated more value-add from their mentor (mean = 4.34) than from student peers in their pod (M = 4.05). Standard deviation was high for peer ratings, indicating a wide range of experiences. Program impact was also well rated (M = 4.31).

Students were able to select multiple options for academic and career motivation. At post-survey, 63% of respondents (n = 169) indicated they were interested in a PhD in computing, and 80% (n = 319) indicated they were interested in pursuing a computing research career in industry. To account for individual students' shifts in academic and career plans (Tables 2 and 3), a McNemar's test showed a statistically significant decrease for students indicating plans to obtain a Master's degree in computing, from 48% to 42% (p = .036) and a statistically significant decrease was seen for the proportion of students who indicated that they would like an academic career in computing, from 43% to 35%, p=.001. For the career options, there was a statistically significant decrease in the proportion of students indicating they are undecided about their future careers, from 10% to 5% (p = .001).

Paired t-tests were conducted for each demographic subgroup to understand if patterns in positive, significant outcomes from the overall sample persisted. Patterns were consistent with the overall sample outcomes (Table 4). All groups show improvements in all survey constructs at post-survey with all but one being statistically significant ($p < .05$). For the BILNW subgroup, the gains in Confidence/self-efficacy were not statistically significant.

To examine individual shifts in academic and career plans, McNemar's tests were conducted for each subgroup. The HMG subgroup had a significant decrease in students indicating plans to pursue an academic career in computing, from 48% to 37% (p = .003), and

Table 2: Graduate school plans from pre- to post-survey

	Pre Count (%)	Post Count (%)	Sig (p)	Count No to Yes	Count Yes to No
MS in computing	191 (48%)	169 (42%)	**0.04**	39	61
PhD in computing	263 (66%)	253 (63%)	0.27	28	38
Consider later	107 (27%)	112 (28%)	0.63	37	32
Not interested	9 (2%)	5 (1%)	0.22	1	5
Not in computing	28 (7%)	28 (7%)	1	15	15

Table 3: Computing career plans from pre- to post-survey

	Pre Count (%)	Post Count (%)	Sig (p)	Count No to Yes	Count Yes to No
Research, industry, computing	336 (84%)	319 (80%)	**0.05**	25	42
Non-research, industry, computing	203 (51%)	184 (46%)	0.08	43	62
Academia, computing	173 (43%)	141 (35%)	**<.001**	27	59
Academia, not computing	35 (9%)	34 (9%)	1	16	17
Research, industry, not computing	61 (15%)	50 (13%)	0.19	24	35
Non-research, industry, not computing	41 (10%)	44 (11%)	0.78	27	24
Undecided	41 (10%)	18 (5%)	**<.001**	9	32

a significant decrease in being undecided about a future career, from 12% to 4% ($p = .001$). Among the FG subgroup, statistically significant proportion changes were observed for plans to pursue a Master's degree, from 44% to 31% ($p = .002$), and for plans to attend graduate school not in computing, from 10% to 4% ($p = .039$). Statistically significant decreases were also observed FGs for seeking a non-research computing career in industry, from 53% to 41% ($p = .021$). Career indecision decreased significantly for FGs from 9% to 4% ($p = .031$).

When asked which of the following steps participants were planning to take following program engagement, the overwhelming majority of students indicated plans to participate in an internship (72%). Half of all students indicated plans to engage in a formal computing research experience (52%). While this percentage was higher for students from the BILNW subgroup (61%), these students indicated the lowest percentage of plans to submit to a conference (37%). HMG students were significantly less likely than the full sample of students to apply to a CS graduate program ($x1 = 4.16$, $p = .041$). BIL students were significantly less likely to submit to a conference ($x1 = 4.19$, $p = .041$).

6 DISCUSSION

A primary contribution of this paper is that a fully virtual, distributed career mentorship program in CS research from industry professionals, focused on socioemotional support and intersectional research capital without direct involvement in a technical research project, has affected positive, statistically significant change that largely persists across intersectional populations for students historically marginalized in the field. This change occurs in key constructs that predict retention in computing, indicating that the program is addressing the preparatory privilege [19] that is a hallmark of the systemic barriers to computing.

We feel this is achieved through the content developed to connect students to resources, opportunities, experts and peers in CS research, and through the information provided to mentors about socioemotional support and Intersectional Capital. Mentors are encouraged to share their challenges and failures to normalize that the CS research pathway is not linear and acknowledge that everyone experiences a variety of difficulties along the way, including current experts, with many experiencing disproportionately greater challenges due to systemic inequities and (un)conscious biases. CSRMP asks mentors to create space for students to share their own difficulties and amplify students' unique experiences and interests as differentiators.

While the improvements in self-efficacy for BILNW students were not significant, they matched the pre-to-post trends of the other demographic subgroups. This improvement is important, regardless of the likelihood of attribution to the program. Significant decreases in intent to pursue a Master's degree, industry research career, and academic careers in computing may reflect changes in students' understanding of degree progression and application (e.g. a Master's degree is not required to enroll in a doctoral CS program, Master's degrees are more technical than research-focused), and that most mentors have PhDs and currently work in industry, and provide advice and insight accordingly. Industry research may appeal to some students, decreasing their interest in academic careers, while not appealing to others, decreasing their interest in industry research. Regardless, significant shifts in any direction and a significant reduction by half in career indecision indicates that CSRMP is helping students gain information to plan their careers in line with their goals and values. Given that the program is open to first and second year undergraduates, including students pursuing Associate's degrees, many have no prior knowledge of graduate school or research; they may express interest in both at pre-survey, and realize that other directions are appealing to them once they are more informed. Additionally, students who have no prior research experience may improve self-efficacy and sense of belonging related to persistence in CS, but still be unfamiliar with hands-on research such that their research career interest may drop due to ambiguity. Further, students may learn of CS careers that interest them, but are not research positions or do not require advanced degrees. There are also many factors outside of the program that influence students' academic and career goals that cannot be captured in the programs' evaluations. The goal of the program is not to convince every student to pursue graduate school and research careers, but to provide students the opportunity to be immersed and build connections in CS research to progress if they so choose. Program

Table 4: Demographic subgroup means from pre- to post-survey

Constructs	All Students (n= 400)		HMG (n=217)		BIL (n=99)		BILNW (n=38)		FG (n=106)		SWD (n=42)	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post
Confidence	4.05	**4.37***	4.03	**4.36***	4.16	**4.54***	4.04	4.32	4.00	**4.32***	3.68	**4.04***
Skills	3.31	**4.05***	3.34	**4.07***	3.36	**4.15***	3.16	**4.04***	3.29	**4.08***	2.99	**3.69***
Community	3.72	**4.16***	3.68	**4.14***	3.73	**4.21***	3.59	**4.12***	3.68	**4.18***	3.30	**3.87***
Capital	3.45	**4.17***	3.43	**4.16***	3.42	**4.25***	3.33	**4.19***	3.31	**4.17***	3.11	**3.92***

* *Significance (p) at or below .05*

features were highly rated for mentoring and the program overall, showing positive experiences. However, peer mentoring pods received lower ratings with a higher degree of response variability, indicating the subjective nature of those interactions [6]. Bi-weekly polls did not indicate problematic peer interactions. Overall, the majority of students plan to pursue graduate school in computing at post-survey, with 63% indicating plans to pursue a PhD and 42% indicating plans for a Master's degree; a remarkably high number of students given the known computing retention issues among marginalized students, despite possible sample selection bias.

We seek to understand how experiences vary among intersectional populations, and to ensure that the program is not unintentionally creating disparate effects. Finding that BIL students are significantly less likely to submit to a research conference and that students from HMGs are significantly less likely to apply to a CS graduate program indicates the need for mentors to have direct conversations about these activities. The similar patterns across intersectional population groups for overall outcomes is encouraging for program evaluation.

Our findings prompt us to explore new user engagement modes, content and resources for mentors, and how to increase equity in our outcomes. The forthcoming program cycle will pilot an opt-in platform for students to identify and connect with a broader set of mentors and student peers to help mentees grow and improve their peer community beyond their pod and allow non-mentor Googlers to schedule virtual career conversations (e.g. resume writing, conference preparation). The program currently operates in only the U.S. and Canada, where the program team is located, native to, and highly familiar with the local contexts of higher CS education and research. In order to support students globally, we're actively exploring which elements and artifacts of the program model can be publicly published and/or transferred to other affiliate entities (e.g. affinity groups, professional organizations, university and college systems) who are able to deliver the program within the cultural and academic context of the region, as well as to any program interested in the resources and evaluations we have developed.

Limitations There are methodological limitations inherent in any study involving intersectional identities. This evaluation is about how participants of differing intersectional identity subgroups experience the program, which intends to improve equitable and inclusive computing research career pathways. We recognize that the individual experiences of students' multiple identities within the subgroup classifications are not monolithic and uniform. This type of evaluation constitutes what Rankin and Thomas refer to as a study of intersectional populations, rather than a study of intersectional identities themselves [25]. This investigation is an attempt to utilize demographic categories as proxy measures for intersectional identities. Quantitative studies cannot entirely avoid the 'additive assumption,' i.e. of adding together identity qualifiers [3]. However, this study used multiple overlapping groups of identity categories, in recognition that these are not mutually exclusive identity properties. The focus of this evaluation is to observe any patterns among intersectional identity groups in order to determine what pivots may be needed for the program, not to draw generalizable findings about populations who hold certain identities or about empirical effectiveness of the program model itself.

Future work We continue to run the program, adding new activities and resources, and recently launched mentor pre- and post-surveys and a longitudinal student survey that will be repeated at six and twelve months after a program cycle to identify lasting impact of the program and changed attitudes, behaviors and goals. We are not able to collect demographic data about mentors, but do ask students whether they shared the gender and/or racial/ethnic identity of their mentor. We plan to run further subgroup analyses to understand differences in program experience by Career Topic, current degree pursued, and mentor characteristics, and analyze qualitative data to shed light on students' experiences in their own voices and precise intersections of gender, racial/ethnic, socioeconomic, and ability status identities.

7 CONCLUSION

Google's CS Research Mentorship Program was created to increase the number of students who identify as women, nonbinary, Black, Indigenous, Latinx and/or students with disabilities pursuing graduate studies and research careers in CS. We theorized that career mentorship from industry professionals that respected students' intersectional identities and lived experiences, valuing them as assets to the field while equipping them with actionable skills and scientific capital in research, would positively affect student outcomes in key constructs. Evaluations from the first two cohorts of the program showed statistically significant improvement in self-efficacy, sense of belonging, research skills and Intersectional Capital across demographic subgroups, as well as a desire to pursue academic and career plans in computing research for the majority of students. These findings indicate that the program is working as intended, and we aspire to replicate the program model in additional contexts to further validate the outcomes observed.

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